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THESIS

COMPARING THE PERFORMANCE OF RESIDENT TO DISTANCE LEARNING STUDENT NAVY OFFICERS AT NAVAL POSTGRADUATE SCHOOL

by

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March 2015

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13. ABSTRACT (maximum 200 words)

Earning a college degree is an aspiration of many, and on-line distance learning (DL) is a feasible way to attain that level of education. The Naval Postgraduate School (NPS) offers masters- and doctorate-level degrees to federal government employees via resident and DL means. Does either method of delivery provide a better, or worse, opportunity for strong student performance? Do available student characteristics lead to better performance in one method or the other?

This study analyzed the performance of 2,633 student Navy officers in the NPS Graduate School of Business and Public Policy (GSBPP), the Graduate School of Engineering and Applied Science (GSEAS) and the Graduate School of Operational and Information Science (GSOIS) in the DL and resident formats. The analysis used simple linear models, general linear models, and recursive partitioning to determine which of ten-selected predictors can identify strong or poor student performance. Results of the analysis showed the NPS Academic Profile Code (APC) is a strong indicator of an increased probability of success, while DL students in GSEAS and GSOIS are at greatest risk of poor performance. More research is recommended to determine why those students have difficulty succeeding at NPS.

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COMPARING THE PERFORMANCE OF RESIDENT TO DISTANCE LEARNING STUDENT NAVY OFFICERS AT NAVAL POSTGRADUATE SCHOOL

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ABSTRACT

Earning a college degree is an aspiration of many, and on-line distance learning (DL) is a feasible way to attain that level of education. The Naval Postgraduate School (NPS) offers masters- and doctorate-level degrees to federal government employees via resident and DL means. Does either method of delivery provide a better, or worse, opportunity for strong student performance? Do available student characteristics lead to better performance in one method or the other?

This study analyzed the performance of 2,633 student Navy officers in the NPS Graduate School of Business and Public Policy (GSBPP), the Graduate School of Engineering and Applied Science (GSEAS) and the Graduate School of Operational and Information Science (GSOIS) in the DL and resident formats. The analysis used simple linear models, general linear models, and recursive partitioning to determine which of ten-selected predictors can identify strong or poor student performance. Results of the analysis showed the NPS Academic Profile Code (APC) is a strong indicator of an increased probability of success, while DL students in GSEAS and GSOIS are at greatest risk of poor performance. More research is recommended to determine why those students have difficulty succeeding at NPS.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABET	Accreditation Board for Engineering and Technology
ANOVA	Analysis of Variance
APC	Academic Profile Code
CHINFO	Chief of Naval Information
CQPR	Curriculum Quality Point Rating
CT	Classification Tree
DL	Distance Learning
DMDC	Defense Manpower Data Center
EAC	Engineering Accreditation Commission
EPC	Education Potential Code
FY	Fiscal Year
GLM	General Linear Model
GPA	Grade Point Average
GQPR	Graduate Quality Point Rating
GRE	Graduate Record Examination
GSBPP	Graduate School of Business and Public Policy
GSEAS	Graduate School of Engineering and Applied Sciences
GSOIS	Graduate School of Operational and Information Sciences
IDC	Information Dominance Corps
IRB	Institutional Review Board
IRRA	Institutional Research, Reporting and Analysis
LM	Linear Model
MBA	Master of Business Arts
MOS	Military Occupation Specialty
NCPACE	Navy College Program for Afloat College Education
NEC	Navy Enlisted Classification
NPS	Naval Postgraduate School
NROTC	Naval Reserve Officer Training Corps
OA	Operations Analysis
OIRP	Officer of Institutional Research and Planning

PCS	Permanent Change of Station
PII	Personally Identifiable Information
PO	Provost Oversight
QPR	Quality Point Rating
RP	Recursive Partition
RT	Regression Tree
SIGS	School of International Graduate Studies
SOF	Special Operations Force
SVIB	Strong Vocational Interest Blank
SWO	Surface Warfare Officer
TA	Tuition Assistance
TQPR	Total Quality Point Rating
USNA	United States Naval Academy
VTC	Video Teleconferencing

EXECUTIVE SUMMARY

College education via distance learning (DL) in an online setting is an education path taken by millions of students and offered by thousands of colleges. The Naval Postgraduate School (NPS) has been offering DL courses to federal government employees for over two decades. However, unlike many civilian institutions of higher education, NPS has yet to conduct a comprehensive, full university analysis to determine if students enrolled through its DL program do as well as their resident-student counterparts. This is the first study to do so by analyzing the performance of DL and resident Navy officer students at NPS. In addition, NPS's primary admissions tool, the Academic Profile Code (APC) was examined to determine its ability to predict student success.

This study is an investigation of the performance of 2,633 Navy officers who enrolled in DL and resident programs in the Graduate School of Business and Public Policy (GSBPP), Graduate School of Engineering and Applied Sciences (GSEAS), and the Graduate School of Operational and Information Sciences (GSOIS) at NPS from academic years 2006 to 2014. Student success was defined in two ways: by the student meeting all requirements for graduation from NPS (a Graduate Quality Point Rating [GQPR] of 3.0 or better) and performing well enough to be selected for graduation "with distinction." The opposite of student success, disenrollment from NPS for either academic or administrative purposes, was also analyzed to develop a thorough understanding of both ends of the student-performance spectrum.

This exploration of student performance was done by selecting ten probable predictors that can determine a student's Total Quality Point Rating (TQPR), graduation eligibility, ability to graduate "with distinction," enrollment status, and TQPR of disenrolled students for a total of five possible response variables. Simple linear models (LMs) and recursive partition (RP) regression trees (RTs) were developed to analyze the continuous response variables of TQPR (0.0 to 4.0). General linear models (GLM) with a logit link and RP

classification trees (CT) were developed to analyze the response variables with a yes or no value. In all, a grand total of ten separate models were created to develop a thorough understanding of DL and resident student performance at NPS.

Results of the two LMs, three GLMs, two RTs, and three CTs provided intriguing insight into all of the variables used as predictors. Of the two main predictors of interest, DL was prominent in seven of the ten models, while APC was important in five of the ten models. Notably DL holds no influence in determining high student performance (graduating "with distinction"), while APC is extremely influential. Conversely, DL is a major determinant of poor student performance (disenrollment for NPS), while APC holds minimal sway in determining student failure.

In addition to APC, only a few other variables were singled out as good signals of student success: time between undergraduate degree and NPS attendance (14 years or less), and United States Naval Academy (USNA) graduate status (Yes). Aside from these three predictors, there are very few distinguishable characteristics among successful students at NPS. In contrast, a theme developed identifying poor student performance: Navy Officers taking DL courses in GSEAS and GSOIS were a noticeable majority of those who were disenrolled from NPS.

It is too early to determine the exact reason for this population's lack of student success. One possible explanation is that the students obligate to a DL program without a full understanding of the time commitment required for success. Another explanation is possible inconsistencies in the delivery of the coursework via DL due to the instructor's lack of familiarity with the format. It may also be possible that students and instructors are fully prepared for the DL experience, but the high level of comprehension required for the technical curricula offered by both GSEAS and GSOIS make it very difficult for the knowledge to be transferred effectively via the DL medium. Follow on work is necessary to pinpoint the source of this shortfall.

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I.   INTRODUCTION

Receiving a graduate education is a strong indicator of an individual's personal motivation and professional potential. Earning a master's degree can be considered an unofficial "check in the box" to many, but, for most military officers, doing so also improves promotion opportunities to the next higher paygrade. Unfortunately, the rigid career path of most Navy officer communities does not allow for the opportunity to step away for 18 months or more to attend the resident program at, for example, the Naval Postgraduate School (NPS). Fortunately for these officers, NPS has been a leader in providing distance learning (DL) education to eligible learners for nearly two decades by providing resources such as Elluminate/Collaborate, Video Teleconferencing (VTC), hybrid programs, and more.

In addition to NPS, many civilian institutions have developed vast DL programs and, within recent years, DL has become a substantial source of income for these civilian institutions (Shachar & Neumann, 2010). With a new source of increased income comes a desire to optimize cash flow from that source; therefore DL offerings have become more robust (through more classes offered, more availability, more resources committed, and more opportunities for degrees, all via DL) throughout academia (Shachar & Neumann, 2010). Rather than grow DL programs haphazardly, civilian institutions have performed their due diligence to determine whether or not DL curricula do, in fact, provide an education equivalent to a resident student's education. Many institutions have published studies that explore the effectiveness of DL (Means, Toyama, Murphy, & Baki, 2013).

Today the opportunities for professionals to pursue advanced education concurrently with their careers are nearly limitless via DL, and navy leadership is very interested in expanding DL opportunities for Navy officers. NPS has provided DL opportunities for nearly two decades (Barrett, 1996) but their comparability to resident education has been only loosely monitored. For

example, in 2012, the NPS Office of Institutional Research and Planning (OIRP) released an informational newsletter detailing the disparity in graduation rates for the Fiscal Year 2002–2008 cohorts (2012). The Graduate School of Engineering and Applied Sciences maintains a database of its DL and resident student performance. Aside from descriptive statistics and anecdotal information, an NPS-wide data analysis comparing the effectiveness of an NPS DL education to NPS resident education has yet to be completed. Before moving forward with expanding DL programs at NPS, it is prudent to determine empirically if those who have earned NPS degrees via DL are just as successful in their studies as their resident counterparts.

A.   DISTANCE LEARNING COURSES AT NPS

Naval Postgraduate School (2014) offers DL curricula within three of its four separate schools. The Graduate School of Business and Public Policy (GSBPP) offers Executive Master of Business Arts (MBA) and Program and Contract Management DL degrees. The Graduate School of Engineering and Applied Sciences (GSEAS) administers degree programs in Space Systems, Electrical, and Mechanical Engineering, among others. Degrees in Systems Analysis and Computer Science are offered through the Graduate School of Operational and Information Sciences (GSOIS).

B.   THE ACADEMIC PROFILE CODE

In addition to analyzing any possible differences in student achievement between DL and resident programs, we also looked closely at the NPS Academic Profile Code (APC) and its connection to student success in both DL and resident programs. Used as the prime screening tool for prospective NPS graduate students, the APC is based on each applicant's overall undergraduate performance (graduating grade point average [GPA]), and performance in upper-level calculus and calculus-based physics courses.

Nearly all curricula at NPS have a required APC for admission. Per the NPS Academic Catalog (2014) the APC is a three-digit code that provides details

on each student's success as an undergraduate (based on transcripts) and their projected propensities for success in the respective curriculum. Each digit of a student's assigned APC must be less than or equal to the required APC for his or her curriculum of study. In cases where a prospective student's APC digit does not meet that requirement, the respective department chair (which can be delegated to Program Officers and Academic Associates) can provide a waiver to allow a student into the desired program.

1. APC First Digit

The first digit of an APC indicates overall academic performance based on a recalculated GPA. It incorporates failures and repeated courses from all previous college transcripts. This first digit is derived from the information in Table 1:

Table 1.   APC First Digit code designation by undergraduate GPA
(after Naval Postgraduate School, 2014a).

Code	GPA Range
0	3.60-4.00
1	3.20-3.59
2	2.60-3.19
3	2.20-2.59
4	1.90-2.19
5	0.00-1.89

According to the Naval Postgraduate School course catalogue (2014a), a first digit code of 0, 1, 2 or 3 (as appropriate) is assigned only if transcripts provided exhibit at least 75 semester-hours or 112 quarter-hours of actual graded classroom instruction. Grades of Pass/Fail and Credit/No Credit do not count toward the 75/112-hour requirement.

2. APC Second Digit

The second digit represents the student's mathematical background. All math courses from calculus through post-calculus are considered when evaluating the transcripts for the second digit. A minimum calculus sequence is Calculus I and II. Possible values are shown in Table 2.

Table 2.   APC Second Digit code designation by undergraduate math experience (after Naval Postgraduate School, 2014a).

Code	Meaning
0	Math Major/Minor, Quantitative Economics Degree with B or better average; math taken less than or equal to 7 years ago.
1	Lower Level, Upper Level, Linear Algebra with a GPA of at least a 3.5; math taken less than or equal to 5 years ago.
2	Lower Level, Upper Level with average between C+ and B+; math taken less than or equal to 5 years ago. No Linear Algebra.
3	Lower Level Calculus Sequence with a C or better; or if math taken greater than 5 years ago.
4	Calculus for Business/Social Sciences with a C or better. 1 Lower Level Calculus Course with at least a C-. 2 pre-Calculus Courses with a B+ or better.
5	At least one pre-Calculus with C- or better grade.
6	No pertinent college-level math with a grade of C- or better.

3. APC Third Digit

The third digit represents previous course coverage in science and technical fields according to the criteria in Table 3.

Table 3. APC Third Digit code designation by physics experience (after Naval Postgraduate School, 2014a).

Code	Eng/Tech GPA	Meaning
0	3.00 - 4.00	Accreditation Board for Engineering and Technology (ABET) Engineering Accreditation Commission (EAC) accredited, B.S. Engineering Degree (regardless of time passed)
1	>= 2.30	Non-ABET EAC accredited, Engineering Degree (regardless of time passed)
2	>= 2.30	Any B.S. Technical degree (regardless of time passed)
3	>= 3.00	Completed calculus-based physics sequence with a B average or above
4	>= 2.00	One calculus-based physics course with at least a C
5	<= 1.99	No pertinent technical courses.

a. Engineering Degrees

Engineering degrees include Aeronautical, Computer, Electrical, Mechanical, Materials, Marine, Naval, Ocean, Systems, Industrial, Chemical, Bioengineering, and Naval Architecture.

b. Technical Degrees

Technical degrees include Applied Physics, Engineering Physics, and Physics.

c. General Engineering and Electrical/Mechanical Engineering Technology

These degrees are not counted as engineering degrees or technical degrees for the purposes of calculating an APC.

d. APC Code Requirements

When calculating the APC, if the record cannot meet all the requirements to obtain Code 0 (i.e., GPA is 2.75 but all other requirements are met) the Code drops to a 1 automatically but no further.

A discussion with the NPS Director of Admissions, LtCol(Ret) Susan Dooley, revealed that the actual genesis of the APC as an admissions tool is not documented. The oldest information she has on the APC dates back to 1983. In addition, APC determination requirements for the second and third digit were adjusted during the time span of the collection of the data being analyzed. This was done to better reflect an applicant's education and preparation for the level of mathematic and technical rigor in the programs at NPS.

C. SCOPE OF THIS THESIS

The purpose of this thesis study is to examine NPS entrance requirements and subsequent student performance of U.S. Navy officers to ultimately determine if NPS DL programs are as effective as resident programs. The goal is to understand predictors of student success (determined by looking at student attrition, all graduating Quality Point Ratings [QPRs], and those who graduated "with distinction") in both DL and resident programs. With this, we intend to build on the understanding of how NPS can best ensure the success of its students in either program, and how NPS can expand its DL offerings.

D. RESEARCH QUESTIONS

1. Is the NPS APC a valid predictor of student success in both DL and resident programs?

2. Do graduate students achieve a higher level of student performance in a resident education or in a distance learning education?

3. What student attributes lead to success in distance learning versus resident learning (and vice versa), and how they differ?

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E.   ORGANIZATION OF THIS THESIS

This thesis contains five chapters. Chapter I provides a general overview and background on the area of analysis. Chapter II provides literature and studies relating to DL and resident education and how they contrast. Chapter III discusses the variables used in the regression and classification models for all active and reserve component Navy officers (and a few enlisted personnel) that studied through NPS during the academic years 2006 through 2014. Chapter IV gives the details of building regression and classification models to determine if there is a difference in student performance between DL and Resident students and whether or not the NPS Academic Profile Code is a valid predictor of success at NPS. Chapter V offers conclusions, recommendations for further research and recommendations to improve the DL program at NPS.

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II. LITERATURE REVIEW

If one talks to most Americans today, the term "Distance Learning" will invoke a schema of VTCs and online courses through a university located in some other part of the country, if there even is an existing campus (Bowers & Kumar, 2015). It is easy to assume that DL programs have only existed since the mid-1990s when the available technology allowed for instructors and students to collaborate online via email and message boards. Many forget that a distance learning class can also be referred to as a correspondence course. In fact, the first university to offer any distance learning opportunity is the University of London when it established the University of London International Programmes in 1858 (University of London, 2014).

A. DISTANCE LEARNING ATTRITION

The ability of a student to maintain his or her studies via a Distance Learning program is a well-known challenge to educators involved in DL. It is considered easier for DL students to drop out because they are normally not located at the school. In addition, for Navy officers, being a student is the primary occupation for those in resident status. For those taking courses via DL, it is a duty secondary to the student's primary billet at a Navy command. Dropping out of NPS as a Resident requires new orders for a Permanent Change of Station (PCS), likely to another geographic location (since there are very few active duty billets located in the Monterey, CA area outside of NPS). This is a large, unplanned cost to the Navy's detailing distribution funds. Dropping out of an NPS DL program means only that the Navy officer actually has one less responsibility to complete in addition to already demanding duties. Since NPS DL classes are taken at no fiscal cost to the student Navy officer (they do, however, incur required service for courses attempted), dropping classes does not lead to the burden of personal funds wasted (which DL students experience when dropping classes through civilian institutions).

1. NPS Research

Studies on attrition from NPS (students disenrolled for academic and/or administrative reasons) are virtually non-existent. Therefore, it is no surprise that there have been no studies on DL attrites from NPS. Aside from this fact, the studies on attrition from enlisted training programs, the Naval Academy, Naval Reserve Officer Training Corps (NROTC) programs, and officer training programs (such as flight school) are numerous and a handful of recent studies at NPS have analyzed student attrition from civilian DL programs via the Navy College Program for Afloat College Education (NCPACE) and tuition assistance (TA).

a. Navy College Program for Afloat College Education

NCPACE is a tuition-free education opportunity available to forward-deployed sailors in operational environments offered through a handful of academic institutions in agreement with the U.S. Navy. There are two delivery options available: classroom instruction where the teacher deploys with a large unit, such as an aircraft carrier, or the DL model for those sailors deployed with smaller units (Chief of Naval Education and Training, 2014). Park (2011) analyzed 206,803 NCPACE courses taken between fiscal year (FY) 1995 and 2008 to see how well these deployed sailors complete and perform in the courses taken via classroom and DL models (and how well these students succeeded in their respective careers after course completion, but that is outside the scope of this study). Through her analysis, she discovered that students taking a course through classroom instruction were ten times more likely to complete the course than those sailors taking a course via the DL model.

b. Tuition Assistance

TA is another tool available to sailors (in fact, available to all service-members) to advance their own educations. This differs from NCPACE because each member using TA is able to register for courses at any approved accredited institution and request TA funds to cover the cost of tuition. TA can also be used

at any time by any service member; NCPACE can only be used while the service member is in a forward deployed status. McLaughlin (2010) looked at the course performance of 233,459 sailors using TA to pay for tuition from FY 1994 to 2008. His analysis revealed that sailors enrolled in DL courses are 10.7% points less likely to successfully complete a course than sailors enrolled in resident courses. Mehay and Pema (2010) analyzed the same data set and discovered similar results. By using fixed effects (holding all but one predictor constant while adjusting that one predictor to see how it affects the respondent), they found an 8% lower pass rate in DL courses than in resident courses.

2. Civilian Research

Attrition from DL courses of civilian institutions is a major concern to their respective administrations. Completion rates are an important measure of success in higher education because funding and accreditation are closely tied to enrollment and course quality, respectively (Howell, Laws, & Lindsay, 2004). With statistics showing attrition in DL courses 10–20% higher than resident courses (Holder, 2007); studies have been conducted to determine why DL student attrition is consistently greater than resident student attrition.

a. Howell, Laws, and Lindsay

From the start, Howell, Laws, and Lindsay (2004) argue that any research comparing DL students to resident students is erroneous, the classic apples to oranges comparison. They provided seven situational factors that DL students have in contrast to their resident counterparts:

1. Delayed college enrollment

2. Hold a Graduate Equivalency Diploma

3. Financial independence

4. Have children

5. Single parent

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6.   Part-time college student

7.   Full-time worker during college

According to Howell, et al. students with these characteristics (who are unable to attend the traditional classroom) make up a separate population from resident students and, because of this, DL student samples should only be compared to that of other DL student samples, from either other schools or previous cohorts.

b.   Street

Street (2010) reviews a handful of research papers that attempted to isolate factors that lead DL students to decide to not complete a course. Street discovered a total of nine factors that lead to this decision and grouped them into three major factors:

1. Course Factors
   - Relevance
   - Design
2. Environmental Factors
   - Family Support
   - Organizational Support
   - Technical Support
3. Person Factors
   - Self-Efficacy
   - Self Determination
   - Autonomy
   - Time Management Skills

B. DISTANCE LEARNING EFFECTIVENESS

1. NPS Research

Fortunately two of the three previously cited NPS studies that analyzed attrition from DL courses compared to resident courses also studied the achievement levels of students who did finish their courses and received a grade.

a. *McLaughlin*

McLaughlin (2010) conducted a study of sailors using TA to further their respective educations. He found that DL students, on average, achieved a half letter grade lower than their resident counterparts.

b. *Mehay and Pema*

With a deeper look into the same data, Mehay and Pema (2010) saw a slightly smaller effect in the DL versus resident student scores. "Since the average grade in the sample is 3.18, or slightly above a B, taking an online class reduces this to a 2.92, or slightly below a B" (Mehay & Pema, 2010). In addition, they also found that pass rates in DL History and English courses were lower than for resident courses in the same disciplines.

2. Civilian Research

Civilian institutions of higher education have conducted an immense amount of research looking at how well DL students perform compared to their resident counterparts. Since the online facet of DL has existed in some form for 25 to 30 years, a couple of thousand studies on this very subject exist. These many studies provide other researchers with the opportunity to conduct meta-analyses to analyze the trends and provide a thorough overview to the rest of academia.

a.   Shachar and Neumann

Shachar and Neumann (2010) conducted a meta-analysis by reviewing 1,850 comparative studies (conducted between 1990 and 2010) and, through a very rigorous filtering process, arrived at an analysis of 125 qualifying studies with a total of 20,800 participating students. Of these 125 studies, 87 of them (70%) showed that DL had an overall positive effect. Based on this (and a Chi-Square (df=1) of 32.13, (p<0.0001)) the researchers confidently declared that the DL students outperformed (based on grades) their resident counterparts "across the full continuum of the study period." In closing, Shachar and Neumann boldly stated "the paradigm of the superiority of the [resident] modality over its distance learning alternative has been successfully negated" (2010).

b.   Means, Toyama, Murphy, and Baki

Even though Shachar and Neumann (2013) claimed ultimate victory for the DL education over the resident education model, the argument is not settled. Means et al. (2013) analyzed 99 (out of an initial 522 reviewed) studies that had at least one contrast between DL and resident learning. Of these 99 studies, they were able to calculate 50 independent effect sizes (g). Of these 50 contrasts, they arrived at a mean effect size of +0.20 (p < 0.0001) in favor of DL. Therefore, DL "produces stronger student learning outcomes than learning solely through face-to-face [resident] instruction" (2013).

C.   NPS ACADEMIC PROFILE CODE RESEARCH

A personal interview with Ms. Susan Dooley, NPS Director of Admissions, revealed that her awareness of the Academic Profile Code dates back to no earlier than 1983. A literature review of theses at NPS reveals very little information on the origin of the APC as an admissions tool and predictor of student success at NPS. What can be found in regards to the APC is rather interesting. The earliest study to involve validation of the APC was published in 1985.

1. Blatt

Blatt (1985) is the first published thesis in Calhoun (the NPS Institutional Digital Archive) to discuss and analyze the APC. Blatt analyzed each component of the APC (digit 1, 2, and 3) and student's biographical data against the fourth quarter QPR of 159 Operations Analysis (OA) students at NPS. He used an Analysis of Variance (ANOVA) of a multiple linear regression and found that APC1 (the first digit), time between undergraduate education and commencing NPS studies, Navy officer community, and a student's undergraduate degree were determined to be the most important predictors of success in the OA program at NPS.

2. Graduate Record Examination Comparison

As a side note, Soetrisno (1975) also conducted an analysis of the performance of NPS OA students and used biographical data, the Strong Vocational Interest Blank (SVIB; a psychological test used in career assessment), Graduate Record Examination (GRE) scores, and the Education Potential Code (EPC) to "develop an equation predicting academic performance of U.S. Navy officer students." The EPC appears to have been the predecessor of the APC; therefore at some point between 1975 and 1983 the EPC was discarded for the APC as the primary admissions tool.

Even with the APC as the primary admissions tool, its status was not set in stone. Per direction from the Chief of Naval Information (CHINFO) in September 1985, all students entering NPS from April 1986 to April 1989 were required to take the GRE. The purpose of this was to determine if the GRE score was better than the APC as an indicator of intellectual capability and predictor of success in Master's programs at NPS (Neil, 1989). Three theses were produced in response to this direction.

a.   Barr and Howard

Barr and Howard (1987) were the first NPS students to produce a response to CHINFO's request. They conducted a multivariate analysis of age, sex, years since receiving bachelor's degree, and APC components against the Graduate Quality Point Rating (GQPR) and Total Quality Point Rating (TQPR) of 320 NPS students who had completed their third quarter. They discovered that a student's age, and GRE Verbal and Quantitative scores coupled with the APC first digit is the best predictor of student success. Interestingly, the APC second and third digits were shown not to be useful predictors of academic success.

b.   Transki

Continuing CHINFO's study on the possible use of the GRE as an entrance requirement for NPS, Transki (1988) conducted a multivariate study similar to that of Barr and Howard on 198 NPS students who have completed their sixth quarter. She concluded that the GRE is a much stronger predictor of academic performance and her findings were in agreement with the previous GRE study: age, GRE scores (including Analytical), and the APC first digit were the best predictors of student success. She produced a formula that a selection board could use to determine an applicant's prospective success at NPS with an R^2 of 0.361 and a standard error of 0.225 TQPR points.

c.   Neil

Wrapping up the three year study on the GRE's utility as a predictor of student performance at NPS, Neil (1989) analyzed the performance of 197 NPS students and validated the work of Barr, Howard and Transki, all but confirming the GRE alone as a more effective measure of prospective student success, but even more effective if combined with the APC. She produced an adjusted equation to better determine an applicant's prospective success (that includes all APC digits and three of the GRE categories) at NPS that has an R^2 of 0.414 and a standard error of 0.285 TQPR points.

3. APC Summary

Despite the three-year study and three empirical theses demonstrating the GRE as a strong supplement to prediction of student success, the GRE is not currently required for admittance to NPS. There appears to be no existing documentation of the decision to forego the use of the GRE and maintaining the APC as the primary metric for entrance into programs at NPS.

D. LITERATURE REVIEW SUMMARY

The literature review displays a stark contrast in the results of civilian DL to resident education studies when compared to Navy DL versus resident education studies. Civilian studies and meta-analyses hold that there is no measurable difference in the success of students in DL when related to resident student success. The Navy studies indicate that DL students significantly perform worse than resident students in TA and NCPACE education programs when reviewed.

The literature reviewed for distance learning attrition and effectiveness focused on undergraduate education data while the APC reports focused on graduate education. In addition to examining the APC, this study also focuses on the attrition and effectiveness of DL and resident graduate level education only. It is possible that, due to the caliber of student, there is an unmeasurable disparity between the academic performance of undergraduate and graduate level students.

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III. DATA

The data used to conduct the analysis in this study was provided by the NPS Institutional Research, Reporting and Analysis office (IRRA). The data was received in two master files, Resident student data and DL student data. To maintain personal security measures for each student observed, social security numbers were not part of the data; however each student's Identification Number was in the data. Neither we, nor anyone outside of the NPS Institutional Research, Reporting and Analysis (IRRA) office, were capable of using Student Identification Numbers to identify individuals. Data was further safeguarded as specified in the approved NPS Institutional Review Board (IRB) protocol.

The Resident file contained data on every student who attended NPS between 2008 and 2014. The DL file contained data on every student who enrolled in a DL program through NPS between 2006 and 2014. There were 8,323 observations comprising all foreign and U.S. military students and civilian students. Each student observation contained 67 variables, including:

- U.S. citizenship
- military service
- military pay grade
- designator/Military Occupation Specialty (MOS)
- undergraduate graduation year
- undergraduate degree name
- undergraduate degree granting institution
- NPS graduation date
- Quality Point Rating (Graduate, Curriculum and Technical: GQPR, CQPR, TQPR)
- required Academic Profile Code (APC) for each respective curriculum
- student's APC (Naval Postgraduate School, 2014a)
- year started at NPS
- enrollment status
- if graduated "With Distinction"

Considering the fact that the request for this study is specifically for Navy officers only, we reduced the data to Active and Reserve Component Navy

officer students at NPS. In addition, The School of International Graduate Studies (SIGS) does not offer DL programs; therefore all students from that school have been removed from the analysis. There are also no 'Provost Oversight' (PO) DL programs, so the performance of those 74 students was not part of the analysis. This resulted in a total of 2,633 observations analyzed. The two master files (Resident and DL) were concatenated into one master file with an additional column added: Distance Learning status.

A.   PREDICTOR VARIABLES

Of the 68 original variables provided with the data, only 26 were determined to be probable predictors of student success. Many of these 26 columns were highly correlated with one or more other columns.

1.   Distance Learning Status

This is the first of two major predictors of interest in this study. It is a simple binary column detailing if students were enrolled in a distance learning program or attended courses on campus at NPS. Of all the Navy officers to take courses from NPS in the provided time windows, 1,187 were DL and 1,787 were Resident.
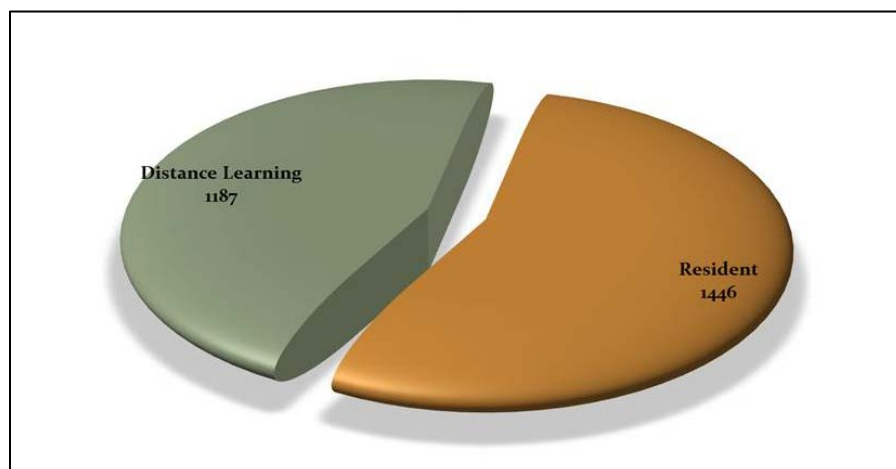
Figure 1.   Breakdown of distance learning and resident NPS students (after IRRA, 2014).

2. Military Pay Grade

The spread of ranks among students taking courses from NPS during the time frame ranged from E-6 to O-7. Even though the request for this study specifically stated Navy officers, we decided to retain the handful of enlisted personnel (6 total; 2 E-6 and 4 E-7) to gain insight on their success at NPS.
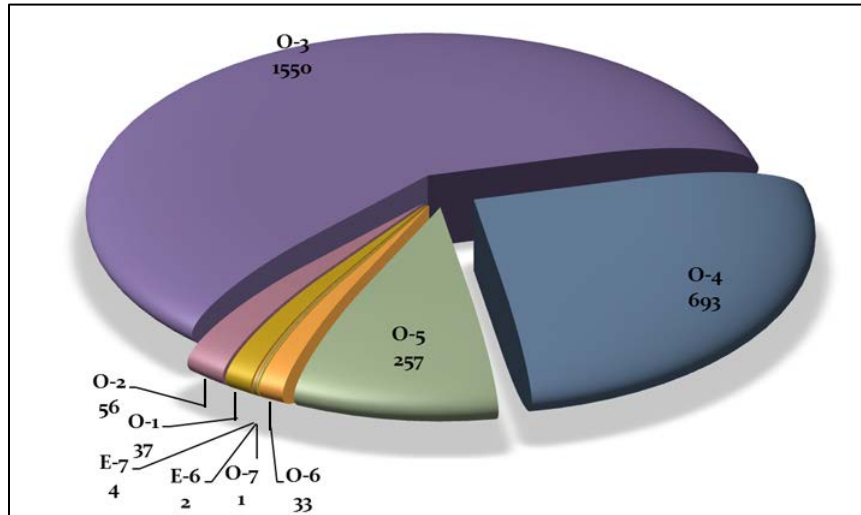
Figure 2.　Breakdown of NPS students' Navy pay grade. The majority of students are of rank O-3 (after IRRA, 2014).

3. Designator/Community

The original column for this predictor listed the numeric designator (i.e. 1110 for Surface Warfare Officer or 1310 for Pilot) for each observation; for enlisted personnel, the Navy Enlisted Classification (NEC) code. This designator column contains 90 separate numeric levels, a number we determined to be too cumbersome and unlikely to provide useful insight. With this in mind, we developed a new column, "Community," and translated each designator to its broader Navy officer community, which resulted in 11 levels (the NEC of the enlisted personnel were all computer network administration/defense skills so we placed all the enlisted personnel into the Information Dominance Corps [IDC]). The "Community" predictor can provide insight into which Navy officer communities have a higher probability of success at NPS.
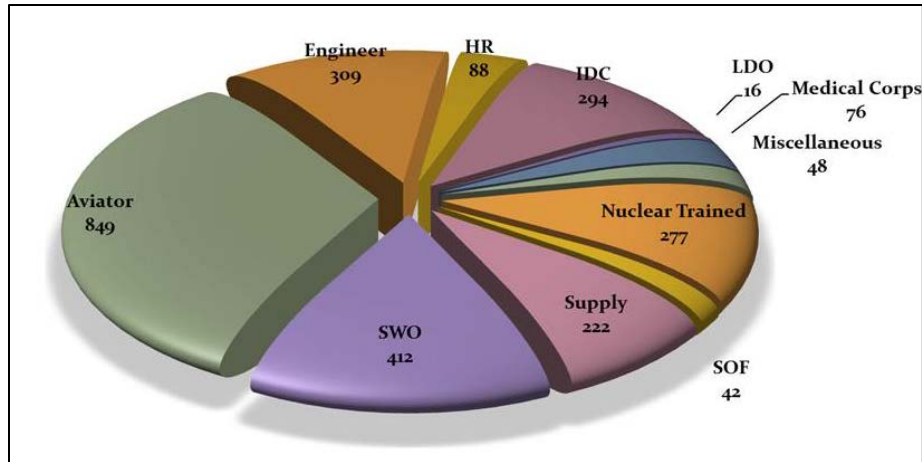
Figure 3.   Breakdown of NPS students' Navy officer Communities. The
majority of students are from the aviation field (after IRRA, 2014).

4.   Undergraduate Degree Year and Start Academic Year

These two separate predictors provide no insight while standing alone, but the difference between the two columns provides the number of years between the time each student earned his or her bachelor's degree and when he or she started working toward a master's degree with NPS. Therefore, we produced a new predictor, "SinceUGrad," that lists the time, in years, between undergraduate completion and starting work on a master's degree with NPS. It is possible that this predictor can have negative correlation with student performance. We also kept "StartAcadYear" in the analysis to see if any variability in student success is dependent on the year the student began his or her studies at NPS.
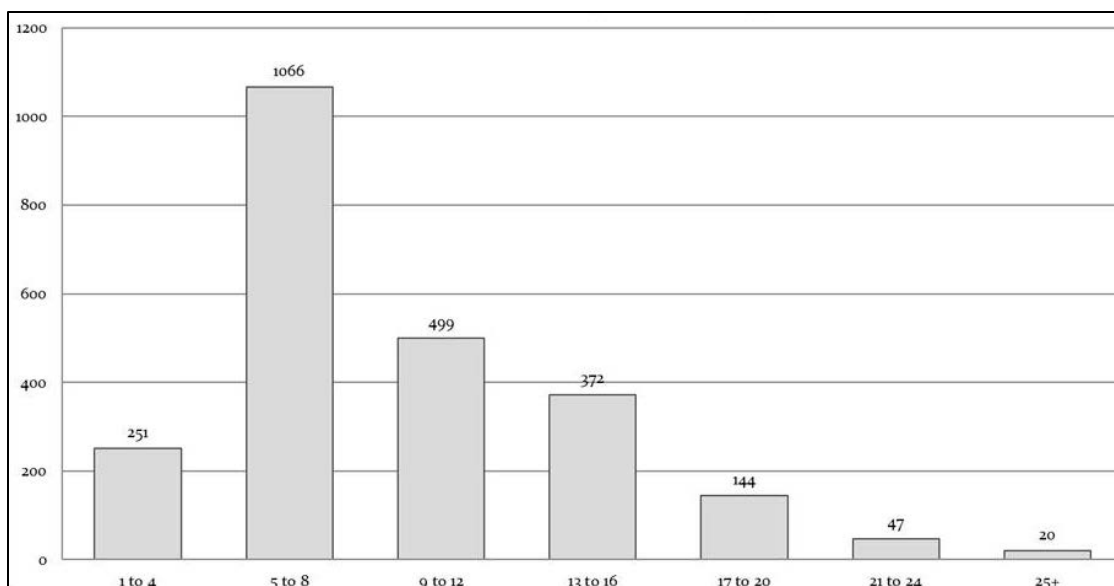
Figure 4.　Distribution of years between undergraduate degree and starting school at NPS. Most students have been out of school for more than 5 years (after IRRA, 2014).

5.　Undergraduate School Name

This column listed each of the 511 separate institutions from which students earned bachelor's degrees. We determined 511 levels to be too cumbersome for insightful analysis so we produced a new column with a binary response: whether or not the student graduated from the United States Naval Academy (USNA). This column, "USNAgrad," can provide insight into whether or not USNA graduates have a greater probability of success at NPS.
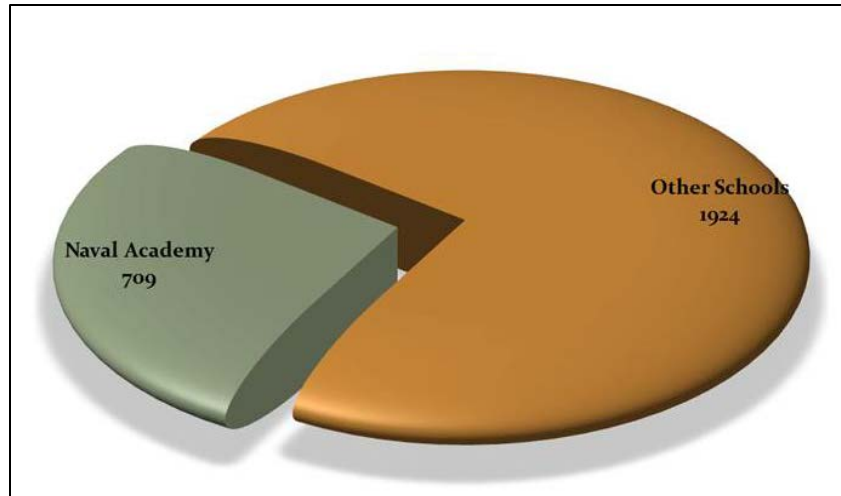
Figure 5.   Breakdown of Naval Academy graduates compared to other secondary institutions of Navy officer NPS students (after IRRA, 2014).

6.   NPS School Name

Given that there are 66 distinct NPS curricula listed in this data, we decided to use the curricula's parent school at NPS. This can provide insight into which of the three NPS schools with DL programs have more successful students.
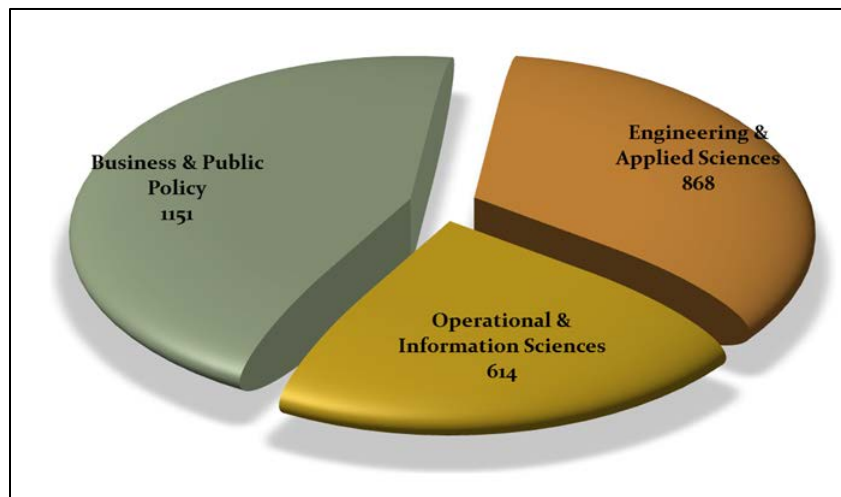
Figure 6.   Breakdown of Navy officer students by NPS school attended. The majority of students study in the GSBPP (after IRRA, 2014).

7. Required APC and Student's APC

This is the second of two major predictors of interest in this study. Given that the APC is a determination of a student's performance in his or her respective undergraduate program and is compared to a baseline APC for each curriculum, it is reasonable to assume that the further from the baseline APC a student's APC is from his or her program's required APC, the better or worse he/she can be expected to perform at NPS. With this in consideration, we produced another column, "APCdelta," that lists the sum of the differences between each digit of the student's APC and required APC. For example, if a curriculum has a required APC of 222, and an applicant has an APC of 112, her APC delta is +2. If another applicant has an APC of 132, his APC delta is 0. In this second case, the -1 on the first digit and the +1 on the second digit do cancel out. This indicates that, even though the applicant's APC is inadequate for one of the APC digits, the other better than required APC digit makes up for that deficit. We recognize that applicant may have required a waiver but, holistically, met the requirement for that program.

The higher the number in "APCdelta," the better the student did as an undergraduate student compared to the APC required by his or her program. The lower number in "APCdelta," the worse the student did as an undergrad compared to the APC required by his or her program. This is expected to produce a positive correlation between the APC delta and student success and provide insight as to whether the APC is a valid predictor of student success at NPS.
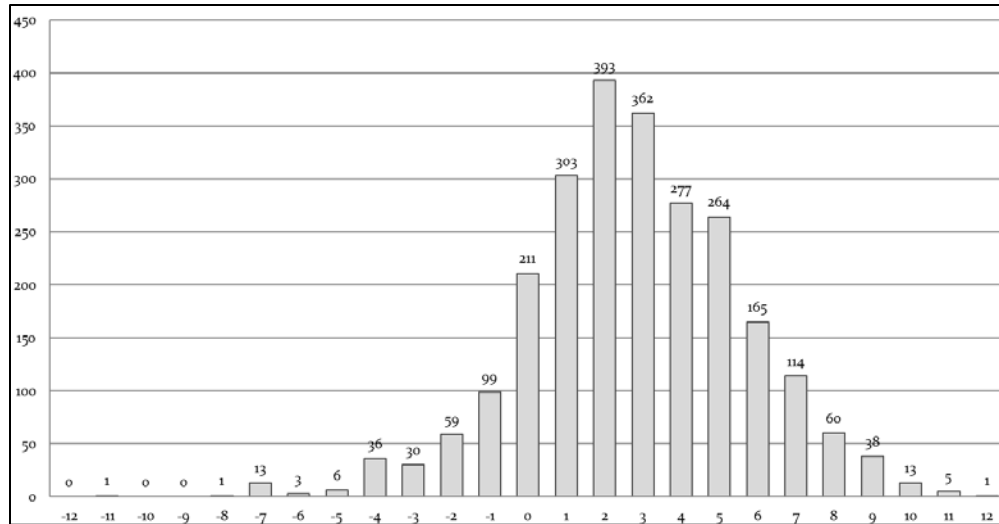
Figure 7.   Distribution of APCdeltas among NPS Navy officer students.
Notice the slightly right-skewed, bell shape (after IRRA, 2014).

8.   Refresher Quarter

This column is a binary indicator of whether or not a student started his or her time at NPS with a refresher quarter.

> This [refresher quarter] is a sequence of courses developed by the Program Officer and the Academic Associate to better prepare incoming students for entering a technical curriculum. This course sequence is designed for prospective students who have an Academic Profile Code (APC) that indicates a deficiency in mathematics and/or scientific and technical subject matter (i.e., their APC does not qualify them for direct entry to a technical curriculum) or, in completing their review of the prospective student's academic record, the Program Officer and Academic Associate have concluded that sufficient time has expired since the student's most recent college experience and as such, the student would benefit from the Technical Refresher Quarter. For some students, this may also include courses from the Six-Week Math Refresher. The refresher sequence is normally twelve weeks in length; however, there are occasions when a student may be assigned two quarters of refresher prior to entering a technical curriculum. (Naval Postgraduate School, 2014)

The "Refresher" predictor is expected to have positive influence on academic success at NPS.
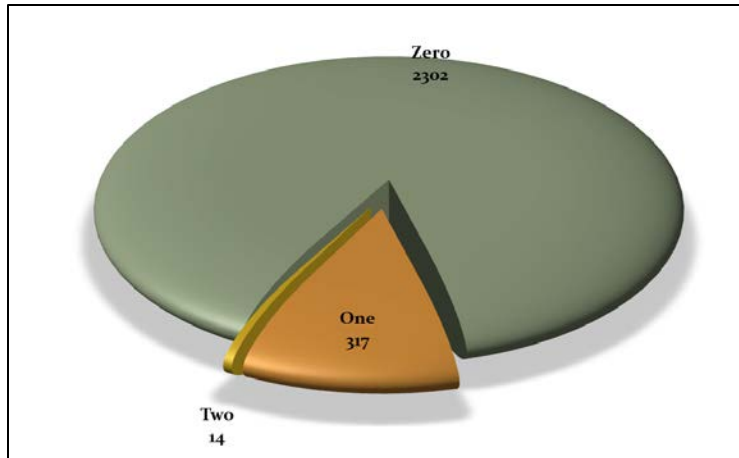
Figure 8.   Breakdown of NPS Navy officer students who took one or more "refresher quarters" before starting official studies (after IRRA, 2014).

9.   Retake Hours and Graduate Retake Hours

Two separate columns in the original data list how many hours each student had to retake while attending NPS. Rather than analyzing the number of retake hours a student achieved, we decided to create a new column, "Retake," that provided a binary response on whether or not the student had to retake any courses. This is expected to have a negative correlation with student success.
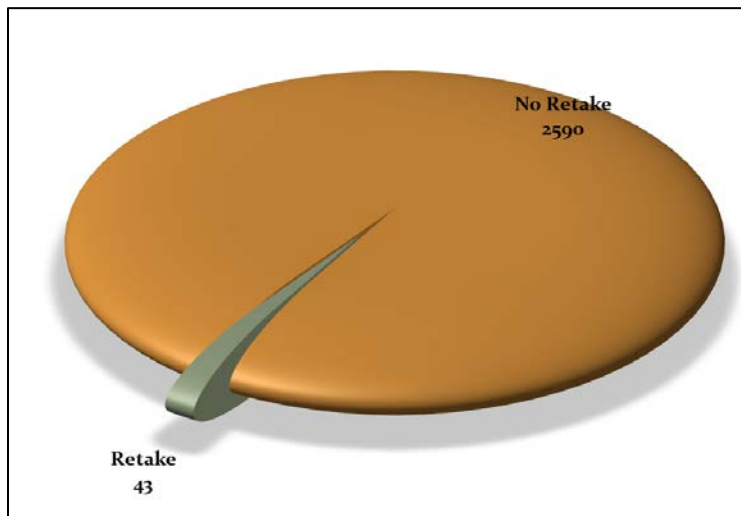
Figure 9.   Breakdown of NPS Navy officer students who had to repeat a class (after IRRA, 2014).

B. RESPONSE VARIABLES

The biggest challenge of this study is selecting the response variable that best represents academic success. Of the 68 columns in the original data, I determined 7 of them to be possible definers of academic success.

1. Quality Point Rating

Generally referred to as the GPA, the QPR at NPS is calculated by taking the sum of the quality points for all courses and dividing it by the sum of the quarter-hour credits for those courses. This gives a weighted numerical evaluation of the student's performance. (Naval Postgraduate School, 2014). NPS tracks three separate types of QPR.

a. Curriculum Quality Point Rating

The CQPR is the QPR calculated for grades received by a student for courses taken as part of his or her designated curriculum.

b. Graduate Quality Point Rating

The GQPR is the QPR calculated for grades received by a student in his or her 3000 and 4000 level courses. Students must have a GQPR above 3.00 to be eligible to earn a degree and graduate from NPS. We created this column by setting all GQPRs below 3.00 to N/A so that we can analyze the population of Resident and DL students that satisfactorily complete their required course of study and if there is any difference between the two groups of NPS graduates.

c. Total Quality Point Rating

The TQPR is the QPR calculated for grades received by a student in all courses taken through NPS. We decided to use the TQPR as the basis for defining student success with QPR because it shows the overall performance of a student with NPS.
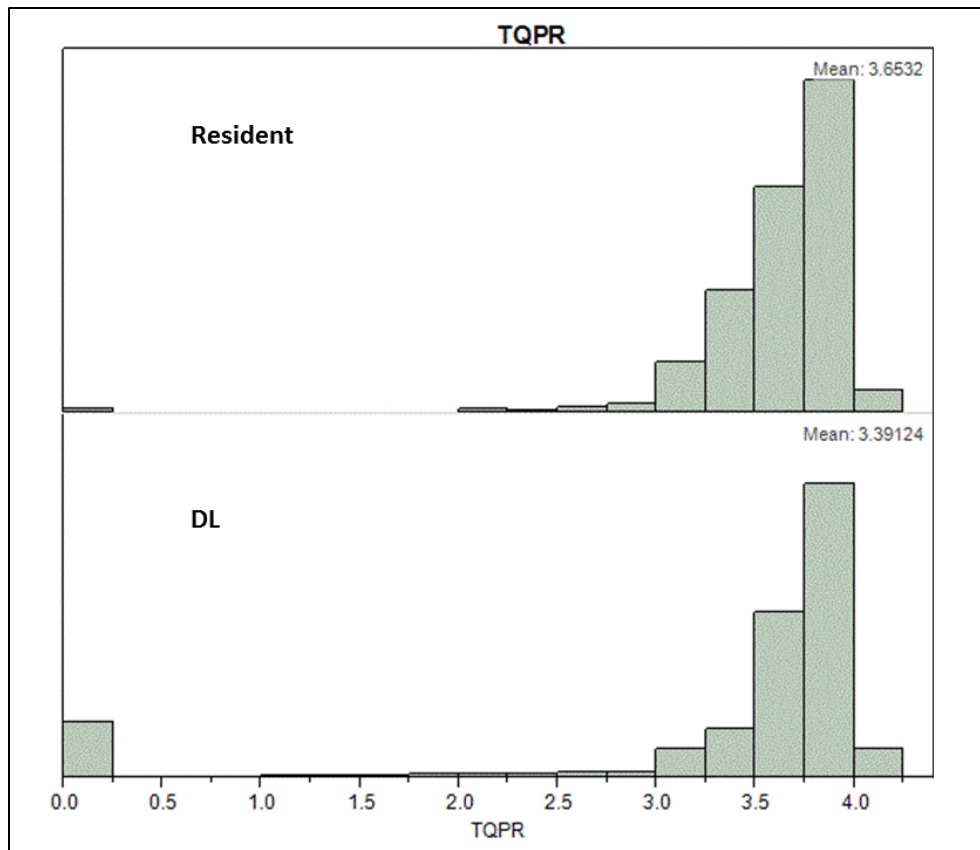
Figure 10.   Distribution of NPS Navy officer student TQPR by resident and DL students. There is a significant number of TQPRs in the 0.0 to 0.5 range on the DL chart (after IRRA, 2014).

2.   Graduation Eligible

This is a binary response listing whether or not a student has a GQPR above 3.0. As per the NPS Student Handbook (2014), a student must have a GQPR above 3.0 and a TQPR above 2.75 to be eligible to graduate from NPS. We decided that GQPR (based on grades in 3000+ level classes) is the more critical of the two.
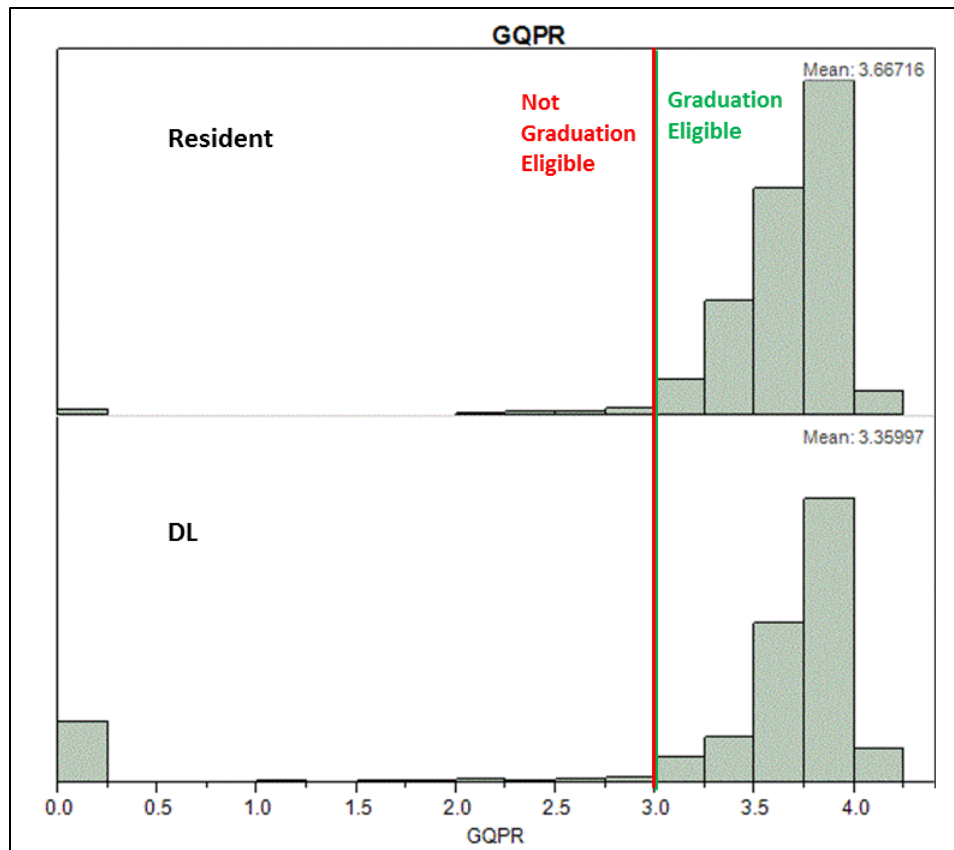
Figure 11.   Distribution of NPS Navy officer student GQPRs with the
"Graduation Eligible" and "Not Graduation Eligible" line at the 3.0
mark (after IRRA, 2014).

3.   "With Distinction"

This is a binary response listing whether or not a student received his or
her degree "with distinction" at the time of graduation. As per the NPS Academic
Policy manual:

> The Academic Council will recommend certain students receiving
> master's degrees to the President for the award of their degrees
> With Distinction. The students must be nominated to the Academic
> Council by the cognizant academic unit. Academic units are
> encouraged to develop criteria beyond the Quality Point Rating to
> evaluate outstanding student performance. To be eligible for a
> master's degree With Distinction, the student must have earned a
> minimum of 24 quarter-hours of graduate level courses presented
> for his or her degree. In any one academic year no more than ten
> percent (or one student, whichever is larger) of the students

earning a master's degree in the degree programs of the nominating academic unit shall be nominated for degrees "with distinction." (Naval Postgraduate School, 2014b)

No more than 10% of graduating students, by school, may selected for graduation with distinction (Naval Postgraduate School, 2014d).
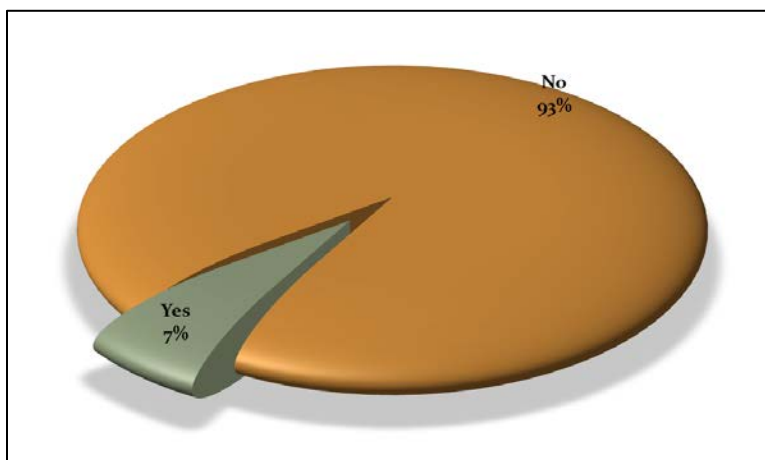
Figure 12.   Breakdown of Resident Navy officer students who graduated "with distinction" (after IRRA, 2014).
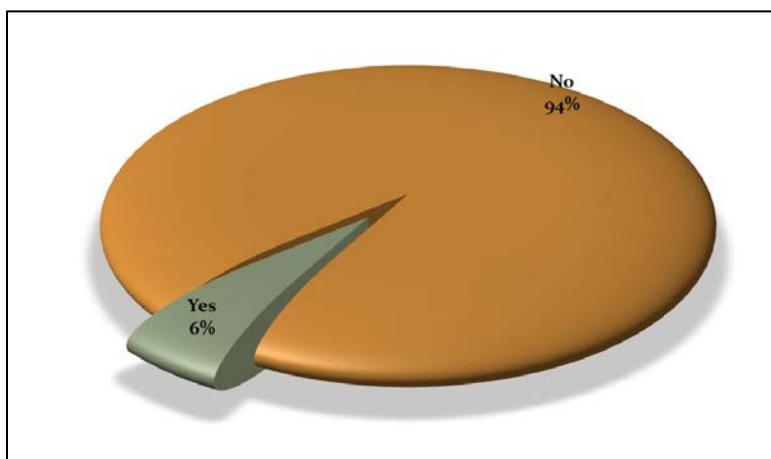
Figure 13.   Breakdown of DL Navy officer students who graduated "with distinction" (after IRRA, 2014).

4. Enrollment Status/Date

These two possible responses are on the other end of the student success spectrum. The "EnrollStatus" column lists each student's positive status (Standard) or negative enrollment status (Disenrolled) either for academic, punitive, or administrative non-punitive reasons. The "DisEnrollDate" column lists the date disenrolled students were released from studies with NPS. I decided to consider any disenrollment from NPS as student failure and therefore produced the column "disenrolled" as a binary response listing whether or not a student was disenrolled. This differs from "Graduation Eligible" because some with GQPR scores less than 3.0 were still in school at the time of data collection and still had the opportunity to raise their GQPR into the graduation-eligible range.
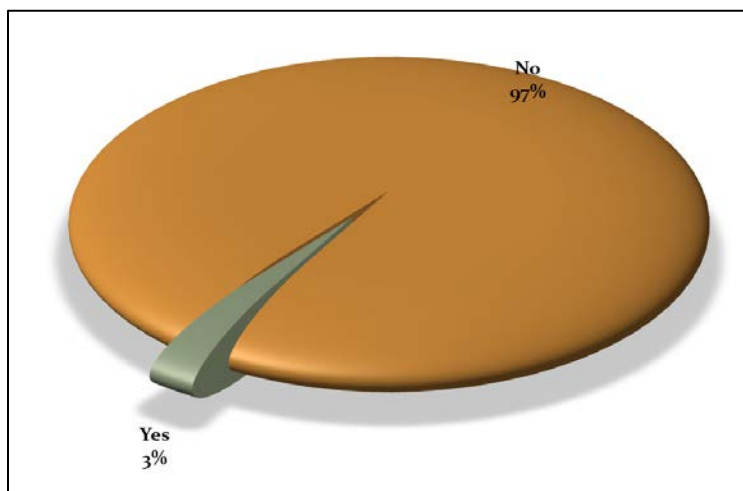
Figure 14.   Breakdown of resident Navy officers students who were disenrolled from NPS (after IRRA, 2014).
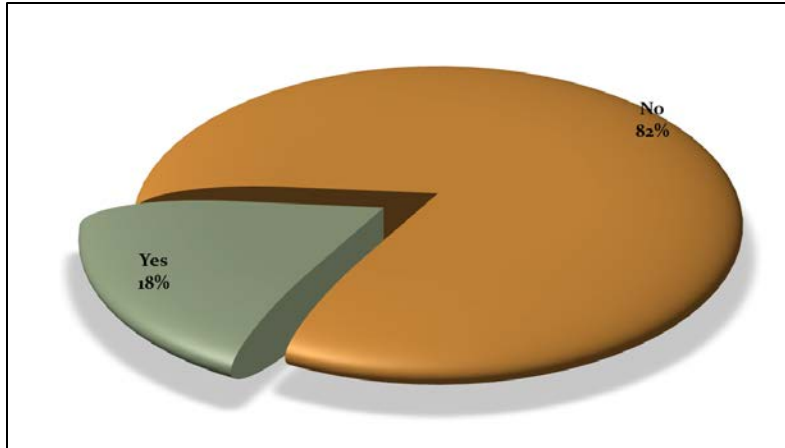
Figure 15.   Breakdown of DL Navy officers students who were disenrolled from NPS (after IRRA, 2014).

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IV.   ANALYSIS

As previously stated, this study has a dual purpose. The first, and overarching, endeavor of this study is to determine, through empirical analysis of the available data, whether or not students from the same population pool (Navy officers) reach equal levels of success in Distance Learning versus Resident education programs at NPS. The purpose of the regression models developed by this study is not to provide predictive capability but to ascertain which predictors significantly contribute to student success or failure. In fact, we aim to find evidence to address the null hypothesis that DL student performance is equal to Resident student performance.

The second purpose of this study is to use the same regression models to maintain the establishment of the NPS Academic Profile Code as a valid predictor of student success by analyzing the students' own APC and its composite deviance from their respective programs' required APC.

"Academic success" is an entirely subjective term; therefore, it is intellectually insincere to select one single metric to define this abstract. To many students working toward a Master's Degree through NPS, the accomplishment of graduation (having a GQPR greater than or equal to 3.00) is considered a success. Others may believe their academic success must be validated with an award such as graduating "With Distinction." Therefore, by using the R statistical computing program (R Core Team, 2014), we developed models to analyze the selected predictors with TQPR and "With Distinction" as the response. In addition, we produced regression and classification trees through Recursive Partitioning with all TQPR data and two subsets of the TQPR data (graduate eligible students and disenrolled students) as the response. The predictors within this model (and all models developed in this study) are listed in Table 4.

Table 4.   Predictor variables used in all models (after IRRA, 2014).

Predictor Variable	Baseline Category	Categories within Model
Distance Learning	No (Resident)	Yes
Pay Grade (factor)	O-3	E-6, E-7, O-1, O-2, O-4, O-5, O-6, O-7
Community (factor)	Surface Warfare (SWO)	Aviation, Submarine, Special Operations, Human Resources, Supply, Engineer, Information Dominance, Medical, Miscellaneous, Limited Duty Officer
Start Academic Year	N/A	2006 to 2012
Since Undergrad	N/A	1 to 38 years
USNA Graduate	No	Yes
NPS School Name	GSBPP	GSEAS, GSEAS
APC Delta	N/A	minus 11 to 12
Class Retake	No	Yes
Refresher Quarter	No	Yes

A.   TOTAL POPULATION

The first look at how any of these ten predictors may affect student success is to develop a simple linear model (LM) with every Navy officer student in NPS colleges that offer resident and DL courses, a total of 2,633 observations.

1.   TQPR as Response Variable

An NPS student's TQPR is a strong indicator of his or her performance in all classes taken through NPS. It directly correlates to a student's final grade in a given class. For example, a grade of A earns four points, a grade of B earns 3 points, while in between those levels, a grade of A-minus earns 3.7 points, and a B-plus earns 3.3 points. This follows suit throughout the rest of the grade spectrum down to a grade of D receiving 1 point. The TQPR is an average of those points earned for all classes taken (Naval Postgraduate School, 2014). A

simple linear regression model is developed with TQPR (a continuous response variable between 0 and 4) as the response. The results of this model are in Table 5. It provides the estimate of the coefficients, the standard error, t-value, and p-value (Pr(>|t|)) for each predictor variable. All information in the following tables are print-outs from the R program.

Table 5. Summary results for the simple linear regression of the total population. TQPR points as response variable. Eleven variables have strong significance (after IRRA, 2014).

Coefficients:	Estimate	Std. Error	t-value	Pr(>|t|)	
Intercept	-5.598	14.445	-0.388	0.698	
DL	-0.323	0.036	-8.971	<2e-16	***
E-6	0.013	0.418	0.031	0.975	
E-7	0.182	0.347	0.524	0.600	
O-1	-0.808	0.160	-5.056	4.64e-07	***
O-2	-0.122	0.105	-1.164	0.244	
O-4	0.103	0.039	2.626	0.009	**
O-5	0.120	0.065	3.083	0.002	**
O-6	0.828	0.145	5.713	1.26e-08	***
O-7	0.800	0.604	1.324	0.186	
Aviator	0.427	0.042	10.134	<2e-16	***
Nuke	0.023	0.058	0.397	0.691	
SOF	0.260	0.102	2.534	0.011	*
HR	0.155	0.076	2.117	0.034	*
Supply	0.152	0.059	2.578	0.100	*
Engineer	0.209	0.050	4.213	2.62e-05	***
IDC	0.272	0.049	5.586	2.60e-08	***
Med	0.243	0.080	3.026	0.003	**
Misc	0.202	0.114	1.771	0.770	.
LDO	-0.107	0.185	-0.580	0.562	
Start Acad Year	0.005	0.007	0.643	0.520	
Since Ugrad	-0.024	0.005	-4.908	9.89e-07	***
USNA Grad	0.016	0.029	0.546	0.585	
GSEAS	-0.206	0.037	-5.526	3.66e-07	***
GSOIS	-0.245	0.005	-6.674	3.13e-11	***
APC delta	0.033	0.041	7.043	2.50e-12	***
Refresher	0.064	0.041	1.547	0.122	
Retake	-0.352	0.101	-3.486	0.001	***

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Residual SE: 0.5875 on 2227 df

Mult R^2: 0.1673		Adj R^2: 0.1572
F-stat: 16.58 on 27 & 2227 df		p-value: <2.2e-16

This LM model indicates that, all other variables being equal, a DL student will have a TQPR that is 0.32 points less, on average, than a resident student. The other variable of primary interest shows that a 1 point increase in APC delta is associated with an average 0.03 point increase in TQPR (again, all other variables being equal). In addition to the strong significance of DL and APC delta, the other variables of interest that show strong significance are the military pay grades O-1 and O-6, the Aviation, Engineer, and IDC communities, years since undergraduate degree, graduate school attended, and retaking a class. To ensure thorough analysis, we decided to run an Analysis of Variance (ANOVA) to see how strong each predictor is without every other factor listed. The results are in Table 6.

Table 6. ANOVA table for total population. TQPR LM. Seven predictors have strong significance (after IRRA, 2014).

	Deg Frdm	Sum Sq	Mean Sq	F value	Pr(>F)	
DL	1	12.75	12.75	36.94	1.43e-09	***
Pay Grade	8	26.61	3.33	9.64	3.28e-13	***
Community	10	60.05	6.01	17.40	<2.2e-16	***
Start Acad Year	1	0.12	0.12	0.36	0.550	
Since Ugrad	1	11.05	11.05	32.01	1.73e-08	***
USNA Graduate	1	0.38	0.38	1.11	0.290	
School	2	21.66	10.83	31.37	3.65e-14	***
APC delta	1	16.86	13.86	48.84	3.66e-12	***
Refresher	1	0.80	0.80	2.31	0.128	
Retake	1	4.19	4.19	12.15	5.00e-04	***
Residuals	2227	768.65	0.35			

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

This ANOVA provides evidence that all but three predictors (Start Academic Year, USNA Graduate, and Refresher Course taken) are very significant determinants of a student's TQPR.

The identification of multiple variables as strongly significant and the high F-statistic (16.58 on 27 and 2,227 degrees of freedom) indicates that this model is better than the null, intercept only model. Low multiple and adjusted R-squared (0.17 and 0.16, respectively) values lend credence to the assumption that there is a lot of noise in the data. More exploration is essential to uncover any real insight into the data.

2. Recursive Partitioning (TQPR as Response Variable)

Recursive partitioning is a technique that is used to determine where interactions exist within the data. This method uses a two stage process to build a classification or regression model that can be represented as a binary tree. The first stage determines which single variable best splits the data into two groups by maximizing the reduction in Gini impurity, "a measure of how often a randomly chosen element from the set would be incorrectly labeled if it were randomly labeled according to the distribution of labels in the subset" (Strickland, 2014). Once the data is split, this same process determines the next level of best split for each successive group of variables. This can continue until no improvement can be made. To avoid developing an overly complex model (which provides no insight), the second stage uses cross-validation to "trim back the full tree" (Therneau & Atkinson, 2014).

The first stage in recursive partitioning can be conducted by the computer while the second stage requires the analyst to determine where the cross validated error is the lowest and provides a regression tree (RT) that clearly shows where the important interactions occur. The results of this process for the TQPR response variable are in Figure 16. It provides the hierarchical position of each node and its successive child nodes, which variable is split and where, the

number of observations in that node, the deviance of the observations within that node, and the average value of the respondent which in this case the TQPR.
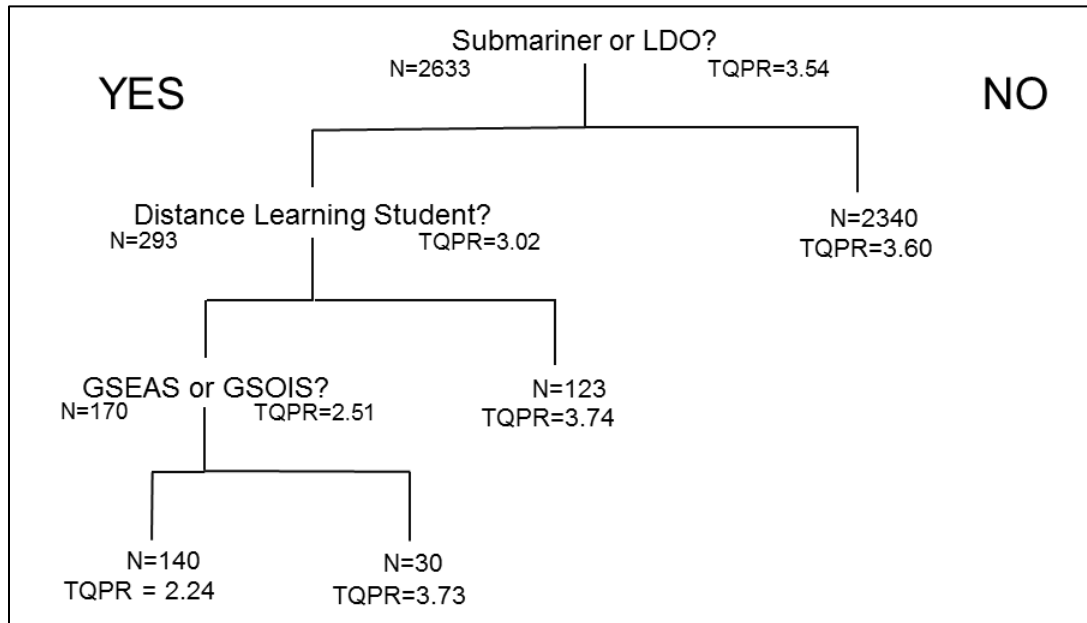
Figure 16.   RP regression tree of the total population. TQPR as response variable. Average TQPR of 140 DL students in GSEAS and GSOIS is 2.24 (after IRRA, 2014).

One can see in Figure 16 that the first single variable that best splits the data into two groups is Navy officer community, where Submariners ("NUKE") and Limited Duty Officers ("LDO") are identified as a significant group. All other Navy officer communities are grouped together and this group ends in a terminal node with an average TQPR of 3.60. The "NUKE" and "LDO" subset continues on to find the second single variable that best splits it. This time it is into DL students (IsDL=Y) and resident students (IsDL=N, which ends in another terminal node, with an average TQPR of 3.74). The last split in this recursive partition is into two terminal nodes. One node has GSBPP alone with an average TQPR of 3.73. The other terminal node is GSOIS and GSEAS with an average TQPR of 2.24.

We can now see an interaction that identifies a subset of the total population with low TQPR: Limited Duty Officers and Submariners in a DL program through GSEAS and GSOIS, a group of 140 students, have an average TQPR of 2.24. This indicates a DL group that does not have academic success.

3. Graduation Eligible as Response Variable

Within this entire population, some students had a GQPR below 3.0; therefore they were not eligible to graduate at the time of the data collection. To see if any of the predictors can identify students that are not able to graduate, we set the binary Graduation Eligible as the response: yes (GQPR greater than or equal to 3.0) or no (GQPR less than 3.0). In addition, the small number of observations of pay grades E-6, E-7, and O-7 were resulting in absurdly large standard errors for those pay grades. Therefore, we suppressed those pay grades in the model to allow for a preferable model.

Given the fact that the response to this model is binary, we calculated the marginal effects (the predicted probability associated with a one-unit increase in a predictor when all other variables are set to their mean values) to determine how much influence each variable has on the result. This was done by using the R package "mfx" (Fernihough, 2015). The results of this model are shown below in Table 7. It provides the estimate of the coefficients, the marginal effect, the standard error, z-value, and p-value (Pr(>|z|)) for each predictor variable.

Table 7. Summary results for the binomial LM of the total population. "Graduation Eligible" as response variable. Five variables have strong significance (after IRRA, 2014).

Coefficients:	Estimate	Mrg. Effect	Std. Error	z-value	Pr(>|z|)	
Intercept	-14.765		126.659	-0.117	0.907	
DL	-2.743	-0.057	0.405	-6.779	1.21e-11	***
O-1	-0.964	-0.020	0.724	-1.333	0.182	
O-2	0.663	0.006	0.718	0.924	0.356	
O-4	0.549	0.006	0.401	1.372	0.170	
O-5	1.007	0.009	0.559	1.803	0.716	.
O-6	2.674	0.012	1.107	2.415	0.016	*
Aviator	1.653	0.018	0.362	4.564	5.02e-06	***
Nuke	-0.504	-0.008	0.417	-1.207	0.227	
SOF	0.774	0.007	1.190	0.651	0.515	
HR	1.211	0.006	0.717	1.689	0.910	.
Supply	1.159	0.010	0.817	1.420	0.156	
Engineer	0.632	0.006	0.507	1.245	0.213	
IDC	0.917	0.008	0.484	1.896	0.058	.
Med	2.013	0.012	0.815	2.470	0.014	*
Misc	-0.319	-0.005	0.658	-0.485	0.628	
LDO	-0.678	-0.012	1.019	-0.666	0.505	
Start Acad Year	0.010	0.000	0.063	0.163	0.871	
Since Ugrad	-0.119	-0.015	0.038	-3.129	0.002	
USNA Grad	0.045	0.001	0.285	0.157	0.871	
GSEAS	-1.233	-0.021	0.380	-3.246	0.001	**
GSOIS	-2.112	-0.052	0.350	-6.043	1.51e-09	***
APC delta	0.149	0.002	0.044	3.413	0.001	***
Refresher	0.091	0.001	0.524	0.173	0.863	
Retake	-2.264	-0.095	0.549	-4.210	3.79e-05	***

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Null Dev: 787.16 on 2248 df

Residual Dev: 548.37 on 2224 df

AIC: 598.37

Many fewer predictors are showing strong significance in this binomial response logistic model. The only variables that carried over from the TQPR LM and continue into this model are the Aviation community, GSOIS, retaking a class, DL and APC delta. Since this is a binomial response, we analyze the marginal effects of each variable. In this case, the logistic model indicates that DL students are 5.7% less likely to be graduation eligible; one-point increase in APC delta improves the likelihood of graduation eligibility by only 0.2 percent. The results of an Analysis of Variance (ANOVA) calculated with the 'MASS' package (Ripley, 2015) in R (due to the binomial response) for this model are in Table 8.

Table 8.   ANOVA Table of the total population. "Graduation Eligible" binomial LM. five predictors have strong significance (after IRRA, 2014).

	Deg Frdm	Deviance	AIC	LRT	Pr(Chi)	
NULL		548.37	604.37			
DL	1	606.83	660.83	58.46	2.07e-14	***
Pay Grade	8	559.60	599.60	11.23	0.189	
Community	10	594.20	630.20	45.83	1.54e-06	***
Start Acad Year	1	548.40	602.40	0.03	0.871	
Since Ugrad	1	548.67	612.67	10.30	0.001	**
USNA Graduate	1	548.40	602.40	0.03	0.875	
School	2	588.12	640.12	39.75	2.34e-09	***
APC delta	1	560.31	614.31	11.94	0.001	***
Refresher	1	548.40	602.40	0.03	0.863	
Retake	1	561.37	615.37	13.00	0.000	***

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

This ANOVA table is very similar to TQPR's ANOVA table where the same three predictors are not significant, and the variable "MilitaryPayGrade" was reduced from high significance to no significance at all. This model analyzed the same amount of data as the TQPR LM, therefore the high level of noise still exists, but dividing the model into two separate groups (GQPR less than 3.0 and GQPR greater than or equal to 3.0) has reduced the number of variables that show strong significance.

4. Recursive Partitioning (Binomial Response)

In addition to a continuous response variable, recursive partitioning is also capable of developing a classification tree for a binomial response. The response is either yes or no in all binomial response models produced in this study. The results of recursive partitioning with "Graduation Eligible" (binomial) are in Figure 17. It provides the hierarchical position of each node and its successive child nodes, which variable is split, the number of observations in that node, and the probability of that respondent occurring for a "yes" or "no" response to graduation eligibility.
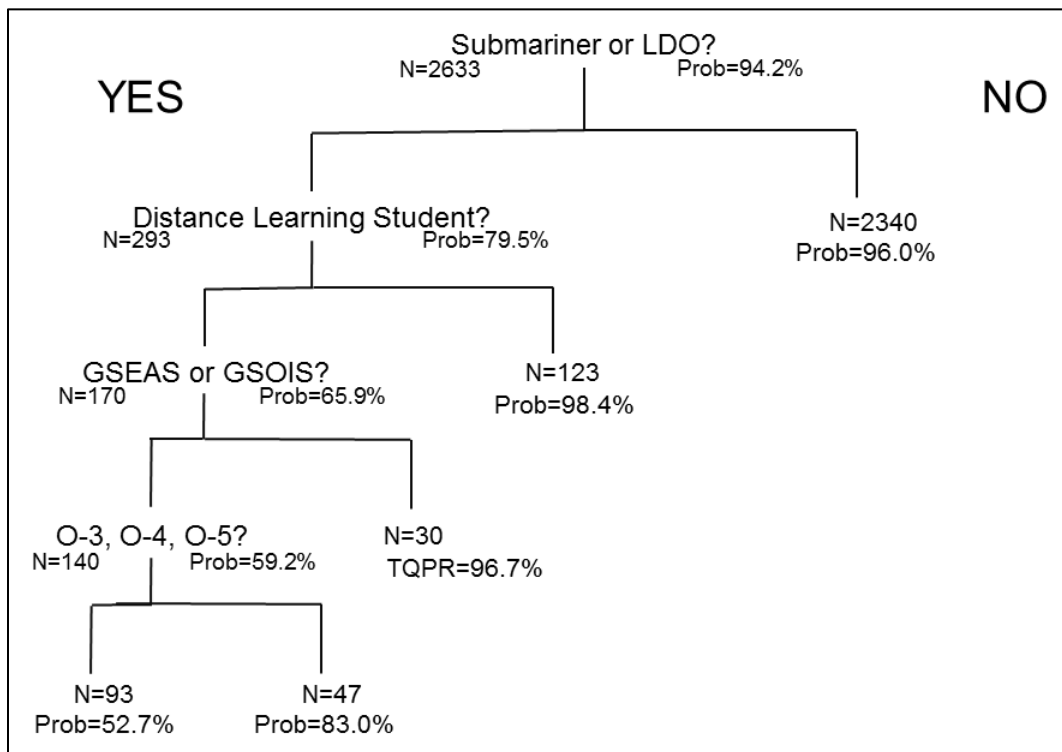
Figure 17.   RP classification tree of the total population. "Graduation Eligible" as response variable. Probability of being graduation eligible for 93 mid-grade Navy officers in DL programs in GSEAS and GSOIS is 52.7% (after IRRA, 2014).

This RP produces a classification tree that goes one step further in complexity than the TQPR response RP by identifying the military pay grades of

O-3, O-4, and O-5 as a group of factors in the "MilitaryPayGrade" variable that have a reduced probability of being graduation eligible. This CT indicates that Submarine and LDO Navy officers of the ranks O-3 through O-5 taking DL courses in either the GSOIS or GSEAS have a 52.7% probability of being eligible to graduate from NPS.

B. GRADUATION ELIGIBLE POPULATION

The previous section considered being able to graduate as a definition of student success. In this section we consider defining student success by examining an award that a student can receive at the time of graduation: "With Distinction." This will be done by analyzing only the subset of the population that is graduation eligible (2479 students).

1. "With Distinction" as Response Variable

The other possible binomial response variable for determining student success is whether or not a student is awarded a "With Distinction" upon graduation (as voted on by respective college faculty). In addition to the pay grades E-6, E-7, and O-7 being suppressed in this model, we also removed the predictor "Retake" for the same reason. None of the suppressed factors or variables were identified significant prior to their removal from this model. The results of this model are shown below in Table 9. It provides the "Estimate" of the coefficients, the marginal effect, the standard error, z-value, and p-value (Pr(>|z|)) for each predictor variable.

Table 9.   Summary results of the binomial GLM with graduation eligible population. "With Distinction" award as response variable. Four variables have strong significance (after IRRA, 2014).

Coefficients:	Estimate	Mrg. Effect	Std. Error	z-value	Pr(>|z|)	
Intercept	139.219		107.187	1.299	0.164	
DL	-0.527	-0.015	0.265	-1.989	0.047	*
O-4	1.021	0.038	0.302	3.387	0.001	***
O-5	2.279	0.172	0.442	5.160	2.47e-07	***
O-6	3.523	0.470	0.810	4.351	1.35e-05	***
Aviator	0.848	-0.030	0.369	2.299	0.215	*
Nuke	1.115	0.052	0.428	2.605	0.009	**
SOF	1.468	0.085	0.592	2.480	0.013	*
HR	-0.551	-0.013	0.812	-0.680	0.497	
Supply	0.235	0.007	0.536	0.439	0.660	
Engineer	1.248	0.058	0.402	3.107	0.002	**
IDC	1.137	0.051	0.412	2.756	0.006	**
Med	0.309	0.010	0.824	0.375	0.707	
Misc	-0.553	-0.012	1.118	-0.495	0.621	
Start Acad Year	-0.071	0.002	0.533	-1.341	0.180	
Since Ugrad	-0.064	-0.002	0.039	-1.667	0.095	.
USNA Grad	-0.064	0.003	0.198	0.486	0.627	
GSEAS	0.046	0.018	0.274	0.169	0.866	
GSOIS	0.294	0.009	0.252	1.167	0.243	
APC delta	0.297	0.009	0.037	7.972	1.56e-15	***
Refresher	0.167	0.005	0.294	0.566	0.571	

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Null Dev: 1112.96 on 2110 df

Residual Dev: 925.47 on 2089 df

AIC: 969.47

Each analyzed military rank is strongly significantly different from O-3, the base level, and the only variable that has retained strong significance following the first two models of this study is APC delta. It shows a 0.9 percent increase in likelihood of graduating with distinction for each one point increase in APC. The marked decrease in significance of DL can indicate that being a DL student is not as detrimental for this high level of student success with only a 1.5 percent decrease in likelihood of the honor for DL students. The results of an Analysis of Variance (ANOVA) for this model are in Table 10.

Table 10.   ANOVA table for graduation eligible population "with distinction" binomial LM. Two predictors have strong significance (after IRRA, 2014).

	Deg Frdm	Deviance	AIC	LRT	Pr(Chi)	
NULL		920.73	976.73			
DL	1	924.92	978.92	4.20	0.041	*
Pay Grade	8	953.42	993.42	32.69	6.99e-05	***
Community	10	945.96	981.96	25.23	0.005	**
Start Acad Year	1	922.76	976.76	2.03	0.154	
Since Ugrad	1	923.17	977.17	2.45	0.118	
USNA Graduate	1	920.90	974.90	0.17	0.679	
School	2	922.54	974.54	1.82	0.403	
APC delta	1	991.06	1045.06	70.34	<2.2e-16	***
Refresher	1	921.01	975.01	0.29	0.593	

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

For the first time, we see smaller significance for the DL variable in the ANOVA table for this model. Interestingly Navy officer Community shows good significance in this ANOVA while no factors show that level of significance separately. APC delta and Military Pay Grade are, once again, very significant. This provides evidence that the "With Distinction" award as a very likely definition of student success for both resident and DL students. Analyzing a smaller subset of the data, only students that are graduation eligible, has provided more insight into what leads to student success.

2.   Recursive Partitioning: "With Distinction"

We discovered that, by using all initial variables, we were unable to produce a noncomplex classification tree (CT). This is due to the fact that RPs can be overly influenced by variables with many factors (Therneau & Atkinson, 2014). Therefore, we removed "MilitaryPayGrade" and "Community" from the model to provide a cleaner CT. The results of recursive partitioning with "With Distinction" as the response variable are shown below in Figure 18. It provides the hierarchical position of each node and its successive child nodes, which variable is split, the number of observations in that node, and the probability of graduating "With Distinction."
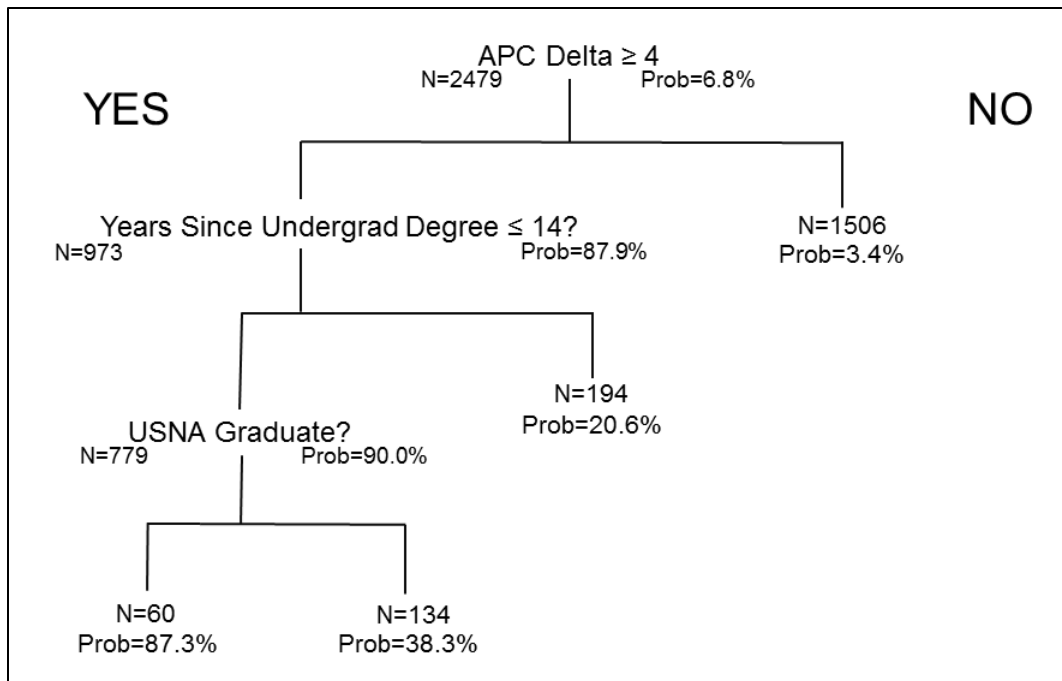
Figure 18.   RP classification tree with graduation eligible population. "With Distinction" as response variable. Navy officers With an APCdelta of 4 or better, who graduated from the USNA less than 14 years have an 87.3% probability of graduating "with distinction" (after IRRA, 2014).

This is the first RP to identify APC delta as an important predictor and it is the best predictor for the first split. This indicates that an APC delta greater than or equal to 4 vastly improves ones opportunity to graduate "With Distinction," from 3.4% to 87.9%. After that, time since graduation (less than or equal to 14 years, which correlates with military pay grade) and USNA graduate status are important. This RP indicates that a student with an APC that is 4 or better, who graduated from the Naval Academy less than 14 years prior to starting studies at NPS has the best chance to graduate with distinction from NPS. What is most important in this RP is the absence of DL. This indicates that DL is not an important predictor when determining this high level of student performance.

C.   DISENROLLED STUDENTS

To best ensure student success, it is advisable to develop a better understanding of students who become disenrolled from studies at NPS (be it for academic or administrative reasons). For this purpose I returned to analyzing the total population (2,633 students).

1.   Disenrolled as Response Variable

The data provides an opportunity to also look at the opposite of student success: disenrollment from NPS. Running a model with this variable as a binomial response provides insight into which predictors may lead to a student failure. We again suppressed the military pay grades of E-6, E-7, and O-7 for the same reason as before. We did, however, bring the variable "Retake" back into this model. The results of this model are shown below in Table 11. It provides the estimate of the coefficient, the marginal effect, the standard error, z-value, and p-value (Pr(>|z|)) for each predictor variable.

Table 11. Summary Results of the binomial GLM with total population. "Disenrolled" as response variable. Four variables have strong significance (after IRRA, 2014).

Coefficients:	Estimate	Mrg. Effect	Std. Error	z-value	Pr(>|z|)	
Intercept	195.902		90.694	2.160	0.031	*
DL	2.301	0.115	0.286	8.046	8.58e-16	***
O-1	1.193	0.076	0.638	1.871	0.061	.
O-2	-0.376	-0.011	0.584	-0.644	0.519	
O-4	-0.277	-0.009	0.282	-0.980	0.327	
O-5	-0.874	-0.023	0.413	-0.211	0.035	*
O-6	-2.752	-0.350	0.968	-2.842	0.004	**
Aviator	-1.373	-0.042	0.267	-5.146	2.67e-07	***
Nuke	0.211	0.008	0.340	0.620	0.535	
SOF	-0.986	-0.023	1.115	-0.844	0.377	
HR	-0.666	-0.018	0.505	-1.321	0.187	
Supply	-1.665	-0.034	0.657	-2.536	0.011	*
Engineer	-0.730	-0.021	0.380	-1.919	0.055	.
IDC	-0.421	-0.013	0.346	.1.219	0.223	
Med	-1.007	-0.024	0.491	-2.051	0.040	*
Misc	0.331	0.013	0.495	0.668	0.504	
LDO	0.434	0.019	0.820	0.530	0.596	
Start Acad Year	-0.100	-0.004	0.045	-2.205	0.027	*
Since Ugrad	0.105	0.004	0.030	3.496	0.001	***
USNA Grad	-0.015	-0.001	0.206	-0.073	0.942	
GSEAS	0.570	0.023	0.251	2.268	0.023	*
GSOIS	0.669	0.028	0.245	2.731	0.006	**
APC delta	-0.095	-0.003	0.031	-3.088	0.002	**
Refresher	-0.513	-0.016	0.437	-1.175	0.240	
Retake	2.514	0.280	0.450	5.584	2.35e-08	***

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Null Dev: 1229.72 on 2248 df

Residual Dev: 951.92 on 2224 df

AIC: 1001.9

This model lends valuable insight into what can lead to student failure as defined by disenrollment from NPS. Of the strongly significant variables, DL students have an 11.5 percent greater likelihood of disenrollment than their resident counterparts. A one-point increase in APC delta is associated with only a very slight 0.3 percent decrease in likelihood of disenrollment. GSOIS students are 2.8 percent more likely to disenroll and the most alarming revelation is that retaking a course increases the likelihood of disenrollment by 28 percent. The results of an Analysis of Variance (ANOVA) for this model are in Table 12.

50

Table 12.   ANOVA table of the total population. "Disenrolled" binomial LM. Four predictors have strong significance (after IRRA, 2014).

	Deg Frdm	Deviance	AIC	LRT	Pr(Chi)	
NULL		951.92	1007.9			
DL	1	1029.72	1083.7	77.80	<2.2e-16	***
Pay Grade	8	969.32	1009.3	17.40	0.026	*
Community	10	1002.08	1038.1	50.16	2.494e-07	***
Start Acad Year	1	956.79	1010.8	4.87	0.027	*
Since Ugrad	1	964.68	1018.7	12.76	0.000	***
USNA Graduate	1	951.92	1005.9	0.01	0.942	
School	2	960.87	1012.9	8.95	0.011	*
APC delta	1	961.53	1015.5	9.61	0.002	**
Refresher	1	953.39	1007.4	1.47	0.225	
Retake	1	976.45	1030.4	24.51	7.41e-07	***

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

We again see strong significance for the DL variable in this ANOVA table. Retaking a course also shows strong significance along with time since undergraduate studies. Notably, NPS school attended and APC delta are slightly less significant than DL and "Retake" in this model. By analyzing the opposite of student success we are noticing which variables are solid indicators in this data set.

2.   Recursive Partitioning: Disenrolled Binomial

The results of recursive partitioning with "Disenrolled" as the response variable are shown below in Figure 19. It provides the hierarchical position of each node and its successive child nodes, which variable is split, the number of observations in that node, the loss within that node, the value of the respondent for that node and the probability of being disenrolled in parenthesis.
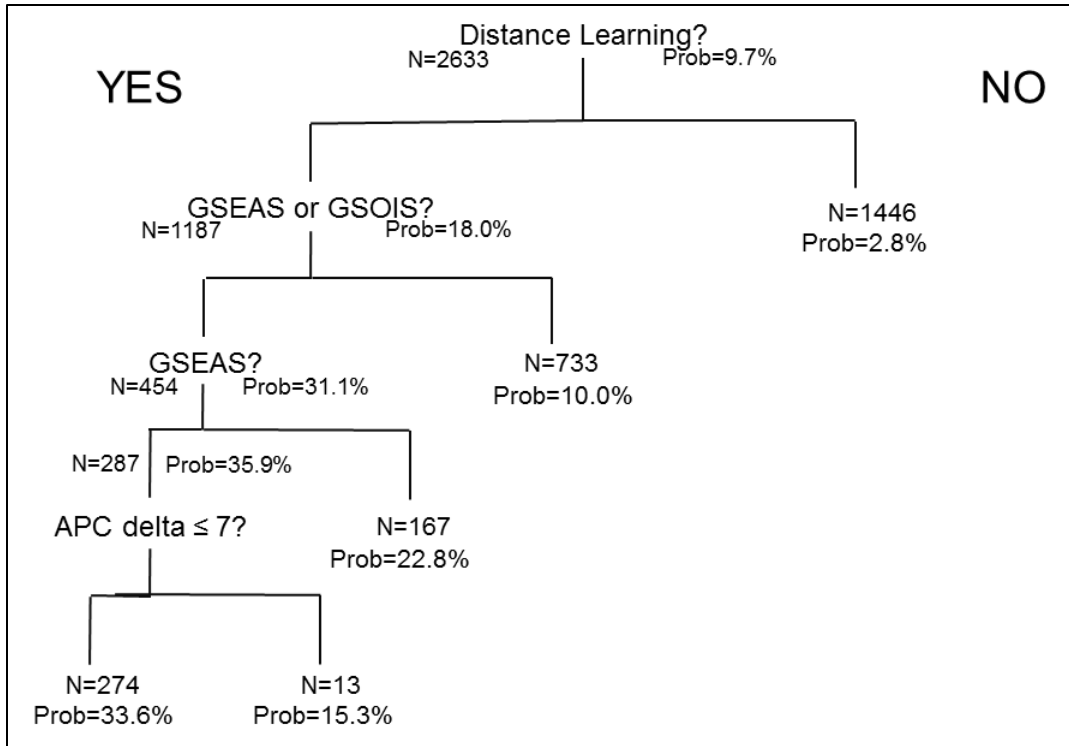
Figure 19.   RP Classification tree of the total population. "Disenrolled" as response variable. Probability of disenrolling for 274 Navy officer students in GSEAS DL programs, with APC delta less than or equal to seven, is 33.6% (after IRRA, 2014).

This RP continues the trend of DL being one of the best predictors for determining response. After that the trend continues by splitting the three schools in two steps. Lastly, APC delta is identified as third best predictor with a split at 7. Interpretation of this CT means that a GSEAS DL student with an APC delta less than 7 has the greatest likelihood of being disenrolled.

3.   TQPR as Response Variable (Disenrolled Student Population)

A necessary follow up to analyzing which students among the total population end up disenrolled from NPS, is to analyze the subset of disenrolled students to see which predictors can signal disenrollment from NPS. The results of this model are shown below in Table 13. It provides the "Estimate" of the coefficients, the standard error, z-value, and p-value (Pr(>|z|)) for each predictor variable.

Table 13. Summary results of the simple linear regression of the disenrolled population. "TQPR" as response variable. One predictor has significance (after IRRA, 2014).

TQPR of Disenrolled Response

Coefficients:	Estimate	Std. Error	t-value	Pr(>|t|)	
Intercept	28.718	111.064	0.259	0.796	
DL	-1.178	0.404	-2.912	0.004	**
O-1	-0.604	0.583	-1.037	0.302	
O-2	0.188	0.677	0.278	0.782	
O-4	0.580	0.329	1.764	0.080	.
O-5	0.590	0.481	1.227	0.222	
O-6	3.143	1.330	2.362	0.019	*
Aviator	0.227	0.318	0.713	0.477	
Nuke	0.095	0.397	0.240	0.810	
SOF	-0.983	1.440	-0.683	0.496	
HR	-0.029	0.610	-0.048	0.962	
Supply	-0.601	0.870	-0.683	0.962	
Engineer	0.034	0.474	0.072	0.943	
IDC	0.177	0.465	0.380	0.705	
Med	0.949	0.603	1.076	0.284	
Misc	-0.152	0.599	-0.254	0.800	
LDO	-0.132	0.783	-0.169	0.866	
Start Acad Year	-0.012	0.055	-0.220	0.826	
Since Ugrad	-0.042	0.032	-1.300	0.196	
USNA Grad	0.218	0.265	0.823	0.412	
GSEAS	-0.839	0.339	-2.477	0.014	*
GSOIS	-1.764	0.311	-5.678	6.86e-08	***
APC delta	0.040	0.034	1.186	0.237	
Refresher	0.481	0.596	0.806	0.421	
Retake	-0.118	0.540	-0.218	0.828	

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

Residual SE: 1.376 on 150 df

Mult R^2: 0.3281	Adj R^2: 0.2206
F-stat: 3.052 on 24 & 150 df	p-value: 1.815e-10

Only one predictor shows strong significance in this model, the Graduate School of Operational and Information Sciences (GSOIS). With all other variables being equal a student who was disenrolled from GSOIS will have, on average, a TQPR 1.76 points less than students in the other two graduate schools. DL may be slightly less significant, but it cannot be overlooked that a disenrolled DL student has a TQPR that is 1.18 points less, on average, than disenrolled resident students. The results of an Analysis of Variance (ANOVA) for this model are in Table 14.

Table 14.   ANOVA table of the disenrolled population simple linear regression. "TQPR" as response variable. One predictor has strong significance (after IRRA, 2014).

	Deg Frdm	Sum Sq	Mean Sq	F value	Pr(>F)	
DL	1	19.78	19.78	10.45	0.002	**
Pay Grade	5	20.43	4.09	2.16	0.062	.
Community	10	19.19	1.92	2.01	0.434	
Start Acad Year	1	3.44	3.44	1.82	0.180	
Since Ugrad	1	8.07	8.07	4.26	0.041	*
USNA Graduate	1	0.04	0.04	0.02	0.884	
School	2	31.89	63.79	16.85	2.511e-07	***
APC delta	1	2.66	2.65	1.40	0.238	
Refresher	1	1.17	1.17	0.62	0.432	
Retake	1	0.09	0.09	0.05	0.828	
Residuals	150	283.97	1.89			

Signif Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '

This ANOVA table is consistent with the summary of this model. School name is very significant and DL status is significant at the 99.9% level.

4. Recursive Partitioning (TQPR as Response Variable)

The results of recursive partitioning with the disenrolled population and TQPR as the response variable are in Figure 20. It provides the hierarchical position of each node and its successive child nodes, which variable is split, the number of observations in that node, and the average value of the respondent.
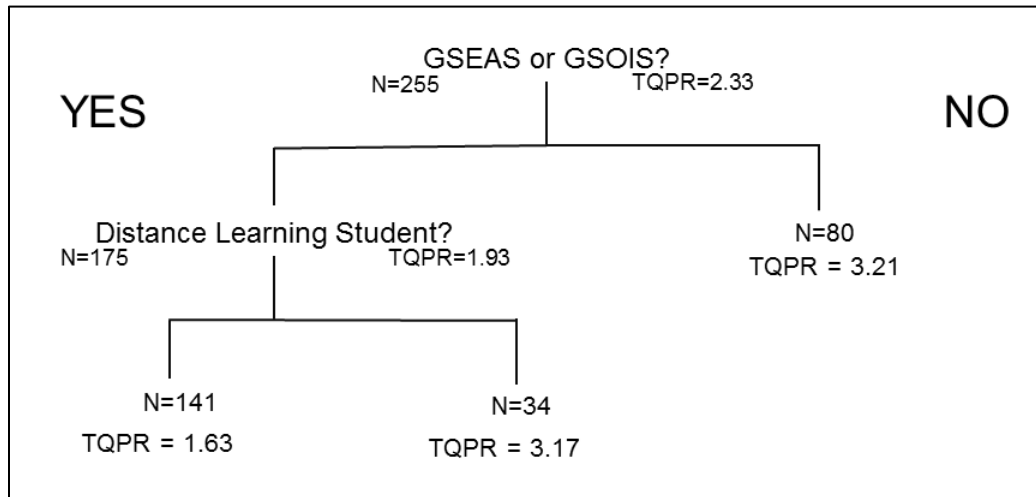
Figure 20.   RP regression tree of the disenrolled population. "TQPR" as response variable. Average TQPR of 141 Navy officer students in DL students in GSEAS and GSOIS is 1.63 (after IRRA, 2014).

This is the shortest, most straightforward and telling of the RPs developed. The first split is between "GSEAS, GSOIS" and "GSBPP." Beneath "GSEAS, GSOIS" is DL status. 141 of the 255 disenrollees (56.47 percent) from NPS were DL students from these schools with an average GQPR of 1.63.

D. ANALYSIS SUMMARY

This analysis produced twelve separate models to explore the data and determine if there is a difference between the performance of DL Navy officer students and resident Navy officer students at NPS. In addition, we looked at each model to see if the APC is a valid predictor of student success. Table 15 is a summary of the results of each model with respect to the two primary predictors of interest: "IsDL" and "APCdelta."

Table 15.   Summary of model results with a Focus on DL and APdelta (after IRRA, 2014).

Model Response	Significant? (Coefficient / Marginal Effect)***	RP Level
TQPR (N=2,633)	<u>DL</u>: Yes (-0.32) <u>APCdelta</u>: Yes (+0.03)	<u>DL</u>: 2 <u>APCdelta</u>: N/A
Graduation Eligible* (N=2,633)	<u>DL</u>: Yes (-05.7%) <u>APCdelta</u>: Yes (+0.02%)	<u>DL</u>: 2 <u>APCdelta</u>: N/A
With Distinction* (N=2,479)	<u>DL</u>: No <u>APCdelta</u>: Yes (0.9%)	<u>DL</u>: No <u>APCdelta</u>: 1
Disenrolled* (N=2,633)	<u>DL</u>: Yes (11.5%) <u>APCdelta</u>: No	<u>DL</u>: 1 <u>APCdelta</u>: 4
Disenrolled TQPR (N=255)	<u>DL</u>: No <u>APCdelta</u>: No	<u>DL</u>: 2 <u>APCdelta</u>: N/A
*logit link and RP classification model	*** >0.001 significance	

For the regression models, Table 15 shows whether a variable was statistically significant at the 0.001 percent level, and if so, the estimate of its numeric (TQPR response) or marginal probability effect (binomial response). For the RP models, we provide the level of the highest split for that variable. Level one means that the listed variable is featured as the root of its respective tree. Level two means that variable is identified as the level immediately below the root, and so on. When 'N/A' is listed, that variable is not identified as important enough to be identified by the RP model.

V. CONCLUSION

A. ANSWERS TO THE RESEARCH QUESTIONS

1. Question 1: Is the NPS APC a Valid Predictor of Student Success in Both DL and Resident Programs?

The predictor "APCdelta" is identified as having very strong significance in determining a student's TQPR (in the simple linear model) and whether or not a student is eligible for graduation. "APCdelta" also has very strong significance in whether or not a student graduates with distinction and is slightly less significant in determining if a student is disenrolled in those two binary response general linear models.

In regards to the recursive partition models, an "APCdelta" greater than or equal to four is identified as the best determinant of whether or not a student graduates with distinction. Conversely, "APCdelta" less than or equal to seven is identified as the fourth most important predictor, and therefore having some association, of whether or not a student is disenrolled from NPS for either academic or administrative purposes.

These two recognitions by the RP model (an APC delta of four or better can lead to great success while one of seven or lower can also lead to disenrollment) make claiming the APC as a valid predictor of student success a little difficult. All three of the APC digits were considered of equal weight in this study. The "gray area" (APC delta scores from four to seven) indicate the necessity for a follow-up study where each APC digit is examined separately to determine which has more effect on student performance. Given that the identification of an APC of four or better ranks at the top of its RP model for graduating with distinction and identification of an APC of seven or lower ranks fourth in predicting disenrollment we have determined that, as a whole, the APC is a valid predictor of student success.

2. Question 2: Do Graduate Students Achieve a Higher Level of Student Performance in a Resident Education or in a Distance Learning Education?

The "IsDL" predictor is identified as having strong significance in all but two of the Generalized Linear Models. The other two LMs ("With Distinction" binomial and TQPR of the disenrolled population) report "IsDL" having slightly less significance (at the 00.1% level). In each model, the direction of correlation is negative when determining TQPR, graduation eligibility, and graduating with distinction. The direction of correlation is positive for both disenrolled LMs. This does not look good for the DL program.

The recursive partitioning models shed some light on which DL students do not perform as well as their resident counterparts. "IsDL: Y" is the most important predictor in determining if a student is disenrolled. It is the second most import predictor in determining TQPR, graduation eligibility, and the TQPR of the disenrolled population. As previously mentioned, RP models are useful for finding where interactions exist without having to manually set up the interactions in a LM. In all but one of the RPs that identify "IsDL" as important, it is followed immediately by the school attended. The school name precedes "IsDL" in the RP of the TQPR of the disenrolled population.

This leads to a mixed answer for this research question. Graduate students in the Graduate School of Business and Public Policy perform equally well in DL and resident programs. DL graduate students in the Graduate School of Engineering and Applied Sciences do not perform as well as their resident counterparts. The greatest disparity between performance of DL and resident students is in the Graduate School of Operational and Information Sciences.

3. Question 3: What Student Attributes Lead to Success in Distance Learning versus Resident Learning (and Vice Versa) and Where Do they Differ?

This study researched two different definitions of student success; achieving eligibility to graduate, and graduating with distinction. We also studied

the opposite of student success by analyzing what could lead to disenrollment from NPS.

a.   *Graduation Eligible*

The predictors and factors listed in Table 15 provide the answer on which attributes aid in reaching the basic standard of student success at NPS. The LM model reveals that Aviation officers do particularly well at NPS and it is best to have a high APC delta. It also shows that DL students, GSOIS students and students that had to retake a course are less likely to have a graduation eligible GQPR. The RP adds to the LM by identifying O-3 to O-5 Submarine Officers and Limited Duty Officers taking DL courses through the GSEAS or the GSOIS have had difficulty maintaining a graduation eligible GQPR.

b.   *Graduating "with Distinction"*

Table 5 provides a summary of the student attributes that can lead to graduating with distinction. Remarkably these are the only models not to identify DL status as strongly significant. The LM is very straightforward; students of pay grade O-4 through O-6 and those with a high APC delta are most likely to graduate with distinction. The RP model is the most complex of all twelve. It agrees with the LM by identifying the APC delta and higher paygrades as the most important predictors and then goes on to list USNA graduates and a handful of officer communities.

c.   *Disenrolled*

Lastly, the summary of the models used to analyze student failure is listed in Table 15. The LM reveals that being a DL student, greater time since undergraduate degree and having to retake a course as increasing the likelihood of disenrollment from NPS and, if disenrolled, it is very likely the student was taking classes through the GSOIS. The RP models are consistent with the LMs; however it is interesting to see that an APC delta greater than or equal to 7 is identified by the RP for which DL students become disenrolled from the GSOIS.

A return look at the summary for this RP reveals that the classification tree identified this group as only 2 of the 255 (0.8%) Navy officer students in the data that were disenrolled from NPS.

B.   POSSIBLE FOLLOW-UP WORK

This is the first study to analyze the performance of distance learning Navy officer students and their resident counterparts at NPS by looking at the population's course grades and academic awards received as definitions of student success. The only data analyzed was academic and career related information provided by the NPS Institutional Research, Reporting and Analysis office. Biographical data such as age, race, gender, etc., was not analyzed; therefore no inference can be made regarding those traits and academic achievement at NPS.

This study was a high-level overview of Navy officer academic performance at NPS. Follow up work more closely analyzing each digit the APC is recommended especially given the fact that the standards for APC2 and for APC3 were adjusted in 2010 and 2012, respectively. Another more in-depth opportunity to analyze this data is to study student performance in curricula within the NPS schools.

The original data contained academic information on all DL students to attend NPS since 2006 and all resident students to attend NPS since 2008. A similar study is possible for analysts interested in other military officer populations, Department of Defense civilian students and all international students. For those researchers willing to take on the responsibility of handling Personally Identifiable Information (PII), it is possible to use this data to link each observation to the actual student, by working with the Defense Manpower Data Center (DMDC), and analyze student career performance after graduating from NPS.

C.   RECOMMENDATIONS

Success at NPS is a very achievable goal for any Navy officer with the desire to continue his or her education and improve his or her value to the United States Navy. Of the 2,974 Navy officers to attend NPS since 2008 and the take classes via distance learning since 2006, only 268 were disenrolled due to academic or administrative purposes.

The Academic Profile Code is a valid indicator of potential student success. Graduating from NPS is a good definition of academic success, but the better definition of a higher level of success is graduating with distinction because it is the only model not to identify DL status and school attended as a strong predictor.

With an better than 90% level of success, and no real distinguishable characteristic that leads to success, it is more efficient to identify the predictors of student failure and determine where NPS can make adjustments to best ensure the success of its students. There is a subset of the student population that this study has identified through valid statistical exploration of the data. There is a common theme among eleven of the twelve of the models developed in this study: DL students in the two technical schools (GSEAS and GSOIS) perform at a level below that of their resident student counterparts.

It is too early to determine the exact reason for this population's lack of student success. One possible explanation is that the students obligate to a DL program without a full understanding of the time commitment required, beyond their full-time jobs, for success. It may also be possible that students and instructors are fully prepared for the DL experience, but the high level of comprehension required for the technical curriculum offered by both GSEAS and GSOIS make it very difficult for the knowledge to be transferred effectively via the DL medium.

One possible solution is to offer a "refresher" quarter to prospective students interested in DL programs in either GSEAS or GSOIS. This refresher

quarter can be offered on a "no commitment to full enrollment" basis. This way, Navy officers that have been out of school for some time have the opportunity to gauge their academic readiness, determine if the study time required fits into their lifestyle, and get a feel for the level of the academic rigor inherent those programs. This refresher quarter can also be beneficial to the instructors to develop teaching skills useful for the DL model.

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